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REVIEW

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Application of artificial intelligence technologies for the detection of early childhood caries

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Abstract
Early Childhood Caries (ECC) is one of the most prevalent non-communicable diseases. It includes a range of environmental and genetic risk factors due to its multifaceted nature. The use of artificial intelligence technologies like Machine learning (ML) and Deep learning (DL) in the field of dentistry helps improve the diagnosis and treatment of ECC. It provides personalized precision in big data and caries prediction. This study mainly focuses on the different risk factors, dental caries indexes, and the importance of early caries prediction and treatment. In this review, we systematically surveyed previous studies on applying ML and DL algorithms for caries prediction. Oral health surveys, longitudinal studies, and databases with dental imaging and demographic data are some of the data sources from these articles. This study examined various approaches, datasets, methodologies, and algorithms. The inclusion criteria are the accuracy of models, the investigation of different risk factors, and the applicability of ML and DL in caries prediction. Results showed that ML algorithms, such as Support Vector Machines, achieved an accuracy of 88.76% on smartphone images, while XGBoost reached 97% accuracy on a health survey dataset, and the Random Forest attained 92% accuracy in a large-scale survey. The DL algorithms, such as the Convolutional Neural Networks, achieved up to 93.3% accuracy on tooth photographs, while Artificial Neural Networks reached 99% accuracy for primary molar caries. By leveraging these technologies, dental care can achieve improved diagnostic precision, early treatment strategies, and personalized healthcare solutions.

Keywords Dental caries, Artificial intelligence, Machine learning, Deep learning

1 Introduction

Early childhood caries, or ECC, is the most common chronic infectious disease in kids, brought on by sugary foods interacting with bacteria on tooth enamel, primarily Streptococcus mutans. The S. mutans can mainly spread to a child from the mother during infancy and infect even predentate babies [1]. ECC is the term used to describe dental decay in babies and young children. The process through which a person's tooth grows over time is known as a carious lesion. ECC may be caused by consuming solid and liquid carbohydrates and acids that lower the plaque's pH and demineralize the enamel [2]. Moreover, dental caries is a multifaceted disease primarily created by a sophisticated relationship between environmental and genetic risk factors. Environmental risk factors include high sugar intake, dental plaque, bad oral hygiene, insufficient salivary flow, and high concentrations of cariogenic bacteria [3, 4]. ECC is also caused by various factors, including nutrition, dental hygiene practices, and oral microorganisms, but it can be avoided by making the necessary behavioural changes [5]. Socioeconomic factors are also risk factors for the early prediction of ECC, like parents' oral health knowledge, feeding style, sugar consumption, the introduction of weaning food, overweightness, and allergies. The prevalence of ECC can be decreased by educating parents about evaluating their children's oral health status and recognizing early indications of the disease, such as high levels of plaque and enamel opacity [6, 7].

The two predominant causes of ECC are microbial and dietary factors; these factors are associated with breast and bottle feeding and are most likely to develop caries in a young child. Feeding while sleeping increases the risk rate since the salivary flow and oral clearance rate decrease while sleeping [8, 9]. "Bottle tooth decay" is a multifactorial disease; dietary practices are considered the leading risk factor [10–12]. There are several risk factors related to this disease: Streptococcus mutans can easily and early colonize the child's oral cavity due to the particular properties of this bacterium and the presence of predisposing factors in the host's mouth [13]. Dietary factors include prolonged absorption of sugars from the liquid. The cariogenic sugars in juices and infant drinks products are actively broken down by the lactobacilli and S. mutans, producing energy, thus forming acids that demineralize the dentine and enamel of the teeth. Dental caries is more common and progresses quickly during childhood and puberty. It demonstrates an epidemiological characteristic that slowly persists beyond puberty, and periodontal disease escalates from adolescence. Therefore, dental caries in children must be treated since undiagnosed juvenile caries can develop into chronic tooth decay and other oral conditions. Preventive and restorative treatments can halt the development of dental cavities. However, long-term treatment is required if it damages the dentin or pulp due to persistent carelessness [14].

ECC is initially identified as a white and dull tooth due to demineralization, rapidly progressing to visible decay along the gingival margin, which is clinically yellow or brown in colour. An older baby whose entire number one dentition has fully erupted may exhibit a significant development of dental injury [15]. Changes in salivary protein components can significantly influence caries resistance or susceptibility. Consequently, modifying the oral microbiota, salivary proteins, and other biomolecules present in saliva influences the growth of oral microorganisms via several innate defence mechanisms. As a result, the protein of saliva could be a volatile indicator of dental fitness [16]. The predictors of early formative years of caries are represented via mediating and moderating factors [17]. Using statistical tools to identify taxa related to caries and their prevalence, with minimal adjustment for societal, environmental, and other influencing factors [18]. The destiny validation of an ECC class may be used similarly to present-day prediction equipment to assist in discovering children at high risk of developing new caries lesions in formative years and adolescence [19].

The Risk Assessment can be conducted to give the basic information required to advise the parents on tooth decay prevention. Children at lower risk may not require restorative therapy. Progressive and cavitated lesions in moderate-risk children may require repair, whereas proximal enamel and white spot lesions must be treated with preventive techniques and progress monitored. To stop the spread of caries, the high-risk children may need earlier restorative intervention for proximal enamel lesions and for progressing and cavitated lesions [19]. Another method for restoring carious lesions in young children is atraumatic restorative treatment (ART), which includes using hand instruments to remove damaged tooth tissue and adhesive restorative materials to fill the cavity [19]. Over 70% of the studies suggested that dental caries in childhood could be treated with fluoride. About 20% indicated more complicated treatment methods, such as endodontics and extraction. Another 10% of studies suggested that physicians should focus on pulp filling and capping [20]. ECC treatment is typically limited to restoration or surgical removal of decayed teeth and dietary recommendations. Different treatment approaches, such as dietary counselling, chemotherapeutic, and fluoride treatments, must be developed that focus on the recurrence-related causative factors, if clinical outcomes improve [8].

1.1 Dental caries indexes

Dental indices are quantifiable methods for measuring, assessing, and analysing the state of teeth in individuals and groups. Groups or individuals use dental indices to determine their health and disease status. Dental indices can include the amount of presence or absence of calculus and plaque in a patient's mouth, the number of existing decayed, missing, or filled teeth, the amount of gum bleeding, the amount of presence of fluorosis, and the amount of movement of tooth over time. Some indices used for the process are the Decayed, Missing, and Filled Teeth (DMFT) Index, the International Caries Detection and Assessment System (ICDAS) score, the Stone Index, the Caries Severity Index, the Caries Susceptibility Index, the Moller Index, and the Nyavad System [22]. A DMFT index is used to assess dental caries in a population. It is the sum of decayed, missing, and filled teeth. The mean of DMFT is the individual sum of DMFT scores divided by the total number of populations. However, they are interpreted as an indicator of dental history rather than health. Moreover, patients' subjective assessments may differ from professionally developed objective measures [22]. ICDAS is a clinical scoring method for measuring caries activity. Figure 1. shows the schematic diagram of different classification scales for the ICDAS II scoring system ranging from zero to six.

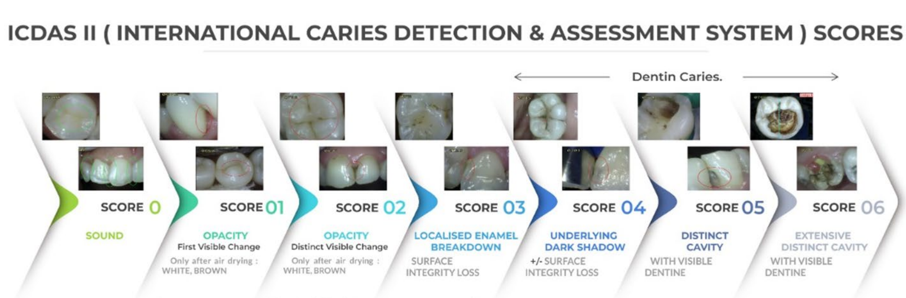

Fig. 1 Schematic diagram illustrating the International Caries Detection and Assessment System (ICDAS II) scoring system, which classifies caries severity on a scale from 0 (sound tooth surface) to 6 (extensive cavitation). The diagram highlights key visual and clinical features associated with each score, aiding in the standardized assessment of caries lesions [21]

1.2 Machine learning for caries prediction

Artificial intelligence (AI) greatly enhances the diagnostic accuracy of early dental caries compared to traditional methods. While conventional techniques such as visual inspection and radiographs can miss subtle carious lesions, AI algorithms can particularly analyze dental images, such as X-rays and intraoral photos, to detect early-stage decay that may be invisible to the human eye [23]. AI offers consistent and objective diagnosis, reducing human error and bias, and can even predict caries progression by assessing risk factors like age, diet, and oral hygiene. Integrated with advanced diagnostic tools, AI provides real-time assistance during clinical procedures, enabling timely interventions. This combination of improved detection, personalized treatment planning, and enhanced clinical decision-making makes AI a transformative tool in the early detection and management of dental caries, ultimately leading to better oral health outcomes [24]. The use of AI in healthcare, including dental caries diagnosis, raises important ethical issues, particularly around data privacy and patient consent. It is essential to ensure that patient data is securely protected to prevent breaches or misuse. Informed consent is crucial, ensuring patients understand how AI works and its benefits and risks. Additionally, the societal impact of AI, such as its effect on resource distribution and traditional healthcare models, should be considered to ensure fairness, transparency, and sustainability in its application. These ethical considerations are vital for protecting patient rights and fostering trust in AI technology [25, 26].

Recent advancements in artificial intelligence, particularly ML and DL, have demonstrated great potential, enabling early diagnostic prediction of ECC using the diverse available datasets. Through the use of algorithms that discover inherent statistical patterns and data structures, machine learning (ML) can anticipate unknown information. ML models offer high prediction accuracy, which is also anticipated to advance diagnostics significantly. Additionally, it can analyze data with various features that traditional analysis cannot, and helps tackle large amounts of complex data in which the correlation of the variables is unclear [6, 15]. Machine learning is designed to enhance learning as it automatically gains experience from example data. It is utilized in various ways in healthcare and has emerged as a crucial tool for comprehending and analyzing extensive data. The ML types are unsupervised learning, supervised learning, and reinforcement learning. By discovering patterns between specific data items, machine learning is a technology used to forecast future events [14]. A training dataset is used to apply machine learning algorithms. The algorithms identify data patterns, build a data mining model, and forecast the outcomes based on the input parameters. Predictions can be made by comparing the model's output to the test data values. ML can support individualised or personalized dental treatment plans and diagnose and evaluate various dental diseases [15].

1.2.1 Logistic regression

Analyzing binary or dichotomous outcomes with two mutually exclusive levels is possible with logistic regression (LR) [27]. There are two critical phases in its data analysis. First, estimates of the model parameters must be obtained, and second, how well the model fits the observed data must be determined. The independent variable, which may or may not be a continuous and dichotomous dependent variable, and a dummy variable with just two possible values, 0 and 1, are subjects of a statistical approach called logistic regression analysis [28].

1.2.2 Random forest

In many research studies, Random Forest (RF) is a widely used ML algorithm for building prediction models. Many T decision trees are combined to form the random forest, an ensemble learning strategy that reduces variance compared to using only one decision tree. RF, based on conditional inference trees [29], tackles the problem of variable selection bias explored [30] and also recognizes the existence of other variants. Random Forest is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and reduce overfitting. Each tree in the RF is trained on a random subset of the data through a process called bagging, and a random subset of features is selected for splitting at each node, a technique known as feature randomization. This makes RF robust for high-dimensional data and resistant to overfitting. In predictive modelling, the goal is to predict and save time and resources by collecting fewer data and using fewer variables [31]. The RF classifier can successfully handle the high dimensionality and multicollinearity of the data. It is fast and a lot immune to overfitting. However, it is sensitive to the sample design [32, 33].

1.2.3 Support vector machine

The Conceptual view of Support Vector Classification (SVC) is that the algorithm seeks the best parting surface (hyperplane) equidistant from two classes. Initially, SVC was applied for low-dimensional surfaces, but to build high-dimensional characters, kernel functions are introduced. Support vector machines (SVM) algorithmically construct the best separation boundaries across data sets by resolving a constrained quadratic optimization problem [11, 12]. Due to their ability to derive detailed analysis of concepts and place constraints on classification errors, SVM has drawn much academic focus in recent years. The literature has reported performances on par with or better than other machine learning methods. Support vector machines have the drawback of producing solely binary classification results without the possibility of class membership being indicated [34]. The Fig. 2. shows the different machine-learning processes in predicting

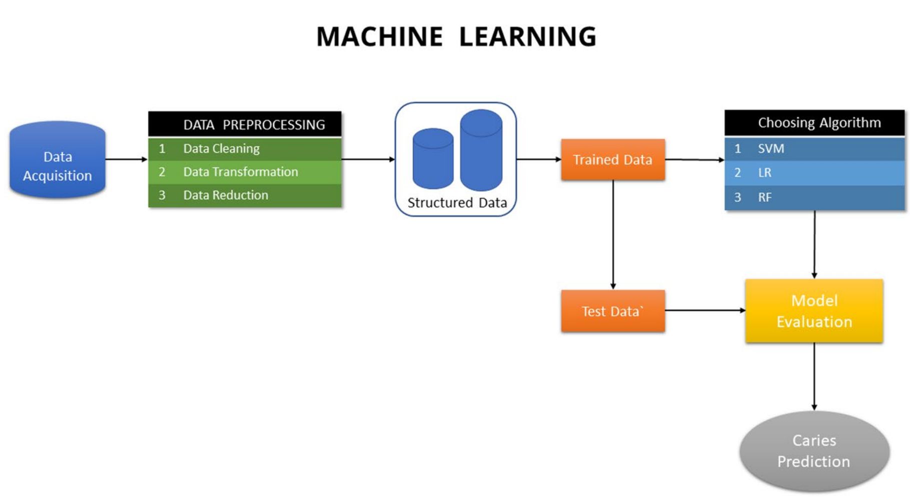

Fig. 2 The schematic diagram shows the different steps involved in the machine learning process for caries prediction [14]

dental caries. Support Vector Machines (SVMs), on the other hand, are powerful algorithms for classification tasks, particularly in high-dimensional spaces. SVM uses kernel functions (e.g., linear, RBF, polynomial) to transform data into higher dimensions and finds the optimal hyperplane that maximizes the margin between classes. Hyperparameter tuning is critical for optimizing ML models. In random forest, the key hyperparameters include the number of trees, maximum depth, and minimum samples per split, which are often selected using cross-validation [35]. For SVM, the regularization parameter (C) and kernel-specific parameters (e.g., gamma for RBF) are tuned to improve model accuracy. Training procedures for ML models involve data preprocessing, such as normalization and handling missing values, and cross-validation (e.g., k-fold) to evaluate model performance and prevent overfitting. These steps ensure that ML models are both accurate and generalizable for caries detection tasks [36].

1.3 Deep learning for caries prediction

Deep learning enables simulation models to handle numerous layers to learn data with varying abstraction levels, and it also helps the computer to build complex concepts from simple ones [37, 38]. One example of the DL method is Near-infrared fluoroscopy (TI) imaging, which has recently been demonstrated to detect early-stage lesions effectively. Moreover, Early detection improves prognosis and decreases the necessity of surgical interventions [39]. Using DL algorithms like image classification, different images are classified and grouped based on their characteristics. Likewise, Dental illness and infections are detected just by using the teeth images; conventional neural networks are used [40]. Deep Learning (DL) models, particularly Convolutional Neural Networks (CNNs), are highly effective for image-based caries detection because they can automatically extract relevant features from dental images. Additionally, transfer learning is commonly employed, where pre-trained models like ResNet and VGG are fine-tuned for caries detection tasks. This approach reduces the need for large datasets and improves model performance, especially in resource-constrained settings. These methodologies make DL models highly accurate and adaptable for early caries detection.

1.3.1 Convolutional neural network

Convolutional neural networks (CNN) with layers that use convolution to extract characteristics. Its convolution process only pools and processes neighbouring data. Convolution, rectified linear unit, and the feature detection layer carry out pooling operations, and by applying a convolution filter to the input data, convolution also contributes to feature activation [8]. The CNN architecture consists of multiple layers, including convolutional layers that apply filters to detect patterns, pooling layers that reduce dimensionality through operations like max-pooling, and fully connected layers that classify the extracted features into caries or non-caries categories. Activation functions such as ReLU (Rectified Linear Unit) introduce non-linearity, enabling the network to learn complex patterns. Optimization techniques like the Adam optimizer are often employed for efficient training [41]. Hyperparameter tuning is essential for optimizing CNN performance, with key parameters including the learning rate, batch size, number of epochs, and filter sizes. Techniques like grid search and random search are used to identify the best hyperparameter values. Training procedures for DL models involve data preprocessing, such as normalization and augmentation (e.g., rotation, flipping), to enhance model generalizability. Cross-validation (e.g., k-fold) is used to evaluate model performance and prevent overfitting. Periodontology can benefit from CNN as an unsupervised diagnostic tool. However, it was severely constrained by hardware limits and the ineffective interaction between the distinct fields of AI and dentistry. A CNN typically accepts a tensor of order as input. It goes through a series of processes like convolution, pooling, normalisation, a fully connected layer, and a loss layer [42, 43].

1.3.2 Artificial neural network

Artificial neural networks (ANN), made up of intricately interconnected adaptive processing units, are viewed as parallel computer simulations of varying complexity. These networks have essential features that appeal to their adaptability, significantly when less understanding of problem-solving, but with available training data and intrinsic parallelism that permits quick computations for the solutions [44]. Artificial neurons, commonly called "nodes," are also composed of essential processing components in ANNs. A "layer" is a collection of 54 nodes organised in a parallel topology. The hidden, output, and input layers are three layers of a simple ANN in which the hidden layer next to the output layer, transmits information to the input layer [45].

2 Methodology

This study systematically reviews the application of machine learning (ML) and deep learning (DL) algorithms for the detection and prediction of early childhood caries (ECC). A systematic search was performed across multiple electronic databases such as PubMed, Scopus, IEEE Xplore, and Web of Science. The search strategy used a combination of MeSH words and keywords with Boolean operators to refine the search results. The key terms included ("Artificial Intelligence," "Machine Learning," OR "Deep Learning,") AND ("Dental Caries," OR "Early Childhood Caries," OR "Tooth Decay,") AND ("Convolutional Neural Network" OR "Artificial Neural Network," OR "Support Vector Machine"). Also, the studies published between 2015 and 2025 focusing on advancements in AI models and their clinical applications in dentistry were considered. Tables 1 and 2 show the inclusion and exclusion criteria considered for the review.

2.1 Inclusion criteria

Table 1 Inclusion criteria for studies on ML and DL in early childhood caries detection and prediction

S. no	Inclusion criteria	Description
1	Focus	Articles discussing the application of ML and DL in ECC detection and prediction.
2	Data sources	Studies with data from oral health surveys, longitudinal studies, and databases with dental imaging and demographic data. Also, the datasets were selected from diverse geographic and socioeconomic groups to enhance the AI model's generalizability and reliability.
3	Accuracy	Studies reporting the accuracy of ML and DL models in predicting ECC.
4	Publication type	Articles published in peer-reviewed journals.

2.2 Exclusion criteria

Table 2 Exclusion criteria for studies on ML and DL in early childhood caries detection and prediction

S. no	Exclusion criteria	Description
1	Focus	Articles that do not focus on ML or DL applications in dentistry.
2	Data or methodology	Studies that lack sufficient data or methodology details.
3	Publication type	Non-peer-reviewed articles and opinion pieces.

3 Results and discussion

Machine learning (ML), the artificial intelligence engine, has significant consequences for public health [15]. ML benefits progress by improving oral health and overall lifestyle conditions by giving dental professionals a tool to make quick judgments to prevent dental caries in individuals. ML methods assisted in identifying the likely cause (attribute features) of the presence of dental caries. As a result, they could aid in the implementation of ML-based decision and recommendation support systems in diagnosis, preventive measures, and consultation with future patients, which considerably cut down on the time, money, and labour needed to complete a similar task in the present oral healthcare system [14]. The results of a study done by Park YH et al. used four significant variables: the Child's Age, household income, daily brushing frequency, and the mother's DMFT; if the mother's DMFT value was high, the probability of ECC in the child was high. The logistic regression model had the highest Area Under the Receiver Operating Characteristic curve (AUROC) of 0.783 [6]. In another study, the SVM model performed well with Area Under the curve (AUC), accuracy, specificity, precision, and sensitivity values (0.997, 97.1%, 94.3%, 95.1%, 99.6%) and classified the existence/nonexistence of root caries precisely compared to other algorithms used such as Random forest (RF), XG Boost, K-Nearest Neighbors (KNN), and logistic regression (LR). However, the random forest also performed well, but not up to SVM, with an accuracy of 94.1% [15].

In the work of Pang L et al., a caries risk prediction model (CRPM) was built, which consists of ML algorithms like random forest and logistic regression. Besides the variables like "past caries experience," "cariostatic score," "plaque index," "gender," and "whether they were only teenagers in the family," the "past caries experience" is identified as the strongest predictor of individual risk. The random forest performed 0.78 and 0.73, whereas the logistic regression-based CRPM performed 0.70 and 0.74 for the training and test cohorts. This demonstrated that the precision of CRPM built with RF was stable [4]. Related work in developing the RF for a sample assessed by a survey based on caries and active care as resultant variables. The threefold cross-validation approach was used to build the models on the training sets. The mean decreased Gini coefficient (MDG) and mean decreased accuracy (MDA) were used to categorize the various oral health indicators. The Random Forest model set accuracy, sensitivity, and specificity for active caries and familiarity with caries, respectively, 0.71, 0.94, and 0.68 [5]. Similarly, the dental caries prediction (DCP) model, which consists of machine and deep learning methods, was developed in this study to predict dental caries in children. Out of methods like Deep neural networks (DNN) and binary classification, RF outperformed significantly in predicting the results with an accuracy of 92%. To improve model performance, feature calibration is used; all methods experience a drop in performance, excluding random forest [14]. Three ML techniques (SVM, LR, and Naïve Bayes classifier) were used in another study. Out of which, SVM and LR outperformed kernel functions. As a result, LR was typically better in classifying the data with an accuracy of 99.83% compared to the other two. While using new data, 92% accuracy was obtained using SVM and cross-validation [46].

Though LR is better at recognizing bad versus good data, its sensitivity to outliers is high since its cost function deviates more quickly than SVM. Moreover, LR and SVM produce probability values and 0 or 1 values, respectively [32]. Whereas Hung M. used LR since it is considered a traditional ML technique in studies, other methods are used to tolerate overfitting, identify high-dimensional relations for the model, ease of deployment in medical settings, or suitability in the field of machine learning [15]. The SVM method, which offers effective solutions to classification issues without making any assumptions about the distribution and interdependence of the data, is model-free [47]. SVM is well-renowned for its discriminative ability for classification, especially when there are numerous features (variables) and small sample sizes (i.e., high-dimensional space) [48]. Table 3. depicts the data distribution of studies based on machine learning algorithms. Compared to other data mining methods like ANN, RF has an advantage and can be utilized to enhance research model comprehension and performance. The free variable selection prevents it from overfitting the dataset and creates models with high predictive power [14].

Dentists face difficulties detecting caries lesions, and DL models could help clinicians improve reliability and accuracy [51]. The trained neural network detected caries lesions and classified them according to depth, similar to skilled dentists. Notably, although they appear to perform against each other, the neural network may be more sensitive and accurate at identifying caries expansions in the outer dentin. It is essential to research how leveraging the network affects the reliability of disease diagnosis and therapy selection [52]. Table 4. represents the following seven research studies using deep learning algorithms predominantly focused on CNN and ANN. Casalegno et al. [39] trained a CNN-based model using targeted imaging (TI) for automatic identification and detection of dental caries to successfully learn to predict effectively and replicate that of qualified dental experts. The reference and predicted labels significantly concur in the occlusal and proximal regions, with 83.6% and 85.6% Area under the curve (AUC). Lee et al. [39] used the CNN model to evaluate 3,000 apical radiographs and achieved accuracy results of well over 80%, with AUC values ranging between 0.845 and 0.917.

In the work of Zanella et al., an analysis of 189 demographic and dietary characteristics and the dental health of a group of participants is examined through an analysis of these determinants. The oral condition is defined as caries' existence, absence, or restoration. The methodology is carried out by building a dense artificial neural network (ANN) in search of a predictive model capable of categorizing subjects. The loss function, accuracy, area under the curve, and the receiving operating characteristic curve parameters were created to validate the classification model statistically. The obtained results had AUC values of 0.69 and 0.75 and an accuracy of 0.69, which were positively accurate [53]. The study by Javed et al. aims to use iOS software developed on the Artificial Neural Network (ANN) model to predict post-Streptococcus mutans ahead of dental caries excavation. For the current investigation, 45 instances of primary molar teeth with occlusal dentinal caries lesions in children were examined. With an efficiency value of 0.99033, an ANN model with a 4-5-1 architecture of feedforward backpropagation successfully predicted the outcome [54].

Table 3 Comparison of machine learning (ML) methods applied in ECC prediction studies, including algorithms used, datasets, accuracy, and limitations. The table highlights the performance of key algorithms such as support vector machines (SVM), random forests (RF), and logistic regression (LR), along with their respective strengths and challenges in caries prediction

S. no	Authors	Algorithms used	Dataset	Accuracy	Limitations
1.	Duong et al. (2021) [49]	Support vector machine Random Forests K-Nearest Neighbors Gradient Boosted Tree Logistic Regression	587 pre-processed smartphone colour images of extracted molars and premolars were used	1. 88.76%	Small dataset size Limited diversity in image sources
2.	Park et al. (2021) [6]	Logistic regression XGBoost Random Forest Light GBM	Data of 4195 children aged 1–5 years from the Korea National Health and Nutrition Examination Survey data (2007–2018). https://knhanes.kdca.go.kr/knhanes/main.do	1. 78.4% 2. 78.5% 3. 78% 4. 77.4%	Relies on self-reported health survey data, subject to bias
3.	Hung et al. (2019) [15]	Logistic regression XGBoost Random Forest SVM K-Nearest Neighbours	Data were obtained from the 2015–2016 National Health and Nutrition Examination Survey	4. 97%	The dataset is region-specific, limiting global applicability
4.	Pang et al. (2021) [4]	Logistic Regression Random Forest	A longitudinal study of 1,055 teenagers (710 teenagers for cohort 1 and 345 teenagers for cohort 2) aged 13 years, of whom 953 (633 teenagers for cohort 1 and 320 teenagers for the cohort 2) were followed for 21 months. https://www.ebi.ac.uk/ena/data/view/PRJEB43233	1. 74% 2. 78%	Cohort size variation and Loss of follow-up participants impacts outcomes
5.	Masood et al. (2012) [50]	Logistic Regression	A sample of 1830 school children was studied, which comprised 950 (51.9%) boys and 880 (48.1%) girls.	(OR = 1.80, $P < 0.001$)	Limited algorithms used Lacks advanced ML model comparisons
6.	Ramos-Gomez et al. (2021) [5]	Random Forest	The sample consisted of 182 parents/caregivers and children 2–7 years old living in Los Angeles County.	1. 70%	Small sample size and Lack of demographic diversity
7.	Kang et al. (2022) [14]	RF ANN Convolutional Neural Network (CNN) Gradient Boosted Decision Trees (GBDT) SVM LR Long Short-Term Memory (LSTM)	The data used in our study were collected from a children's oral health survey conducted in 2018 by the Korean Center for Disease Control and Prevention. https://www.korea.kr/common/download.do?tblKey=EDN&fileId=188769457	1. 92% 2. 88% 3. 87% 4. 85% 5. 83% 6. 82% 7. 75%	High computational resource demands, Limited generalizability due to region-specific datasets, and Lack of model interpretability for clinical use

Table 4 Comparison of deep learning (DL) models employed in ECC detection studies, highlighting algorithms, datasets, accuracy, and limitations

S. no	Authors	Algorithms used	Dataset	Accuracy	Limitations
1.	Casalegno et al. (2019) [39]	CNN	185 training samples	Occlusal − 83.6% Proximal − 85.6%	Small dataset size limits generalizability and model robustness
2.	Lee et al. (2018) [59]	CNN	3000 periapical radiographic images	Molar = 89% Premolar = 88% Both molar and premolar = 82%	The dataset focused only on specific tooth types, limiting its applicability to broader dental contexts
3.	Zanella-Calzada et al. (2018) [53]	ANN	189 dietary and demographic determinants	69%	Limited accuracy The dataset lacks comprehensive dental records for better insights
4.	Javed et al. (2019) [54]	ANN	Caries excavation was done for all 45 primary molar teeth	99%	Small sample size raises concerns about overfitting and a lack of diversity
5.	Schwendicke et al. (2020) [56]	CNN	226 extracted posterior permanent human teeth (113 premolars, 113 molars) were allocated to groups of 2 + 2 teeth.	74%	Focus on extracted teeth does not mimic in vivo conditions, limiting clinical relevance
6.	Sonavane et al. (2020) [57]	CNN	Kaggle dataset	71.43%	The dataset quality and diversity are limited
7.	Kühnisch et al. (2021) [58]	CNN	Consisted of 2417 anonymized photographs of permanent teeth with 1317 occlusal and 1100 smooth surfaces.	93.30%	Bias due to region-specific dataset Potential lack of model interpretability for clinical use

Also, Deep CNN was employed to find caries in pictures of near-IR light transillumination in Schwindicke et al.'s study. In an experimental trial model, 226 removed posterior permanent human teeth (113 premolars and 113 molars) were installed in a dummy head in groups of 2 + 2. Two skilled dentists used a computerized annotation tool created in-house for each segment to annotate proximal and occlusal caries lesions (on average, $435 \times 407 \times 3$ pixels). The pixel-based annotations were transformed into binary class levels. Using 10-fold cross-validation, they trained and validated the latest CNNs, ResNet50 and ResNet18. During the training phase, we used one-cycle learning rates with maximum and minimum learning rates set at 10^{-3} and 10^{-5}, respectively, and data augmentation. We also used model performance metrics and feature visualization for dentists' suitability features. On tooth segments from Near-infrared light transillumination (NILT) images, both models similarly predicted cavities. The final nine ResNet50 network layers were fully trained using the Adam optimizer with a batch size of 10 and a learning rate of 0.5×10^{-4}. They had a marginally higher AUC with an average AUC (95% CI) of 0.74. Specificity was 0.76, and sensitivity was 0.59. The negative predicted value (NPV) was 0.73, while the positive predicted value (PPV) ranged from 0.63 to 0.74 [56]. Figure 3. shows the different processes involved in applying deep learning methods to detect dental caries.

Apurva Sonavane et al. classified cavitated and non-cavitated teeth with visual images of teeth using CNN and used images from the Kaggle to test the model. By tuning hyperparameters, they achieved a maximum accuracy of 71.43 per cent [57]. O. Meyer et al.

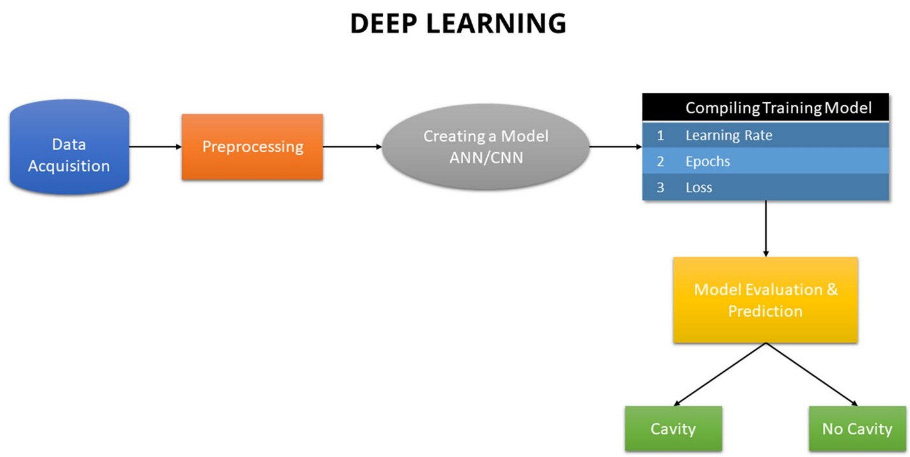

Fig. 3 The schematic diagram showing the different steps involved in the deep learning process for dental caries prediction [55]

presented a study to evaluate diagnostic performance against industry standards. A total of 2,417 unattributed photos of permanent teeth were used in the study, 1,317 of which were occlusal and 1,100 of which were smooth surfaces. The AI algorithms' cycle training and continuous testing used each expert assessment as a benchmark. The CNN was trained via transfer learning and image augmentation. By splitting the data, validation, and statistical analysis, when all test photographs were taken into account, 92.5% of the time, CNN correctly identified caries with an AUC of 0.964. The classification of 93.3% of all tooth surfaces was accurate when the caries-related cavitation threshold was applied with an AUC of 0.955. ANNs are semiparametric nonlinear models that can easily handle massive amounts of data and integrate variables [58].

Some limitations exist while performing the models in the studies; for example, the data was inadequate to build a DNN completely. Data augmentation may lessen overfitting and enhance the model's capacity for generalization. Similarly, the dataset did not distinguish between proximal, root, and early caries and only included permanent teeth [59]. The value is not near zero, but it can be seen that both the data points are still trending in that direction, indicating that the test data declines more slowly than the training data. Adding more data, eliminating unnecessary characteristics for the model, and increasing the number of epochs or the size of the ANN can all help fix this issue [60].

Schwandinke et al. used one of the several accessible architectures while performing only a small amount of optimization and augmentation. Further research could result in greater accuracy, especially if combined with more extensive data [56]. The algorithms are anticipated to perform less accurately when applied to other image types, such as quadrant images, entire lower/upper jaw images, or intraoral images. Additionally, the model's performance depends on the choice of annotator based on their references, which cannot outperform an expert [58]. The importance of diversified data collection from various geographic and socioeconomic groups was emphasized to address challenges in AI-based ECC detection and enhance the model's generalizability and reliability. Due to the non-availability of standardized datasets across different geographic populations, it becomes difficult to compare and implement AI models effectively. This lack of standardization deeply affects the generalizability and robustness of the models, as variations in data collection methods and diagnostic criteria can lead to inconsistencies in model performance. For example, models trained on datasets from one region or demographic group may not perform equally well when applied to populations with different socioeconomic, geographical, or environmental factors. This limitation underscores the need for the development of globally representative datasets that encompass diverse populations and standardized protocols for data collection and annotation. Without such efforts, AI models' widespread adoption and reliability in clinical practice will remain constrained, limiting their potential to improve oral health outcomes globally. While many AI models report high accuracy, the results are often based on retrospective data and may not reflect real-world clinical scenarios. Prospective clinical trials are essential to validate their effectiveness in routine dental practice.

Deep learning models require high computational resources for training and validation, which may not be possible in low-resource settings. To overcome this, developing lightweight-based AI models, utilizing techniques such as model pruning, quantization, and edge computing, can reduce computational costs and make AI more accessible in low-resource settings. These strategies can ensure that AI applications remain scalable, efficient, and applicable across diverse real-world clinical environments, improving their overall utility in ECC diagnosis and treatment. Computer-aided design (CAD) and AI-assisted surgical systems are emerging technologies that help diagnose and treat ECC. With the help of CAD systems, precise dental restorations can be designed, aiding in the planning and executing restorative procedures for carious teeth. When combined with AI, these systems can optimize the design process by automatically adapting to the specific anatomical needs of the patient. AI-assisted surgical systems, on the other hand, can enhance surgical interventions for ECC by providing real-time guidance and improving accuracy in procedures such as cavity preparation or tooth extraction. Together, these technologies streamline the diagnosis and treatment process, offering more accurate, efficient, and personalized care for patients with ECC. Furthermore, explainable AI techniques play an essential role in the identification of ECC by increasing the interpretability of these models. Methods such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations), Grad-CAM (Gradient-weighted Class Activation Mapping), and saliency maps can provide visual or numerical explanations for model predictions, thereby helping clinicians understand why a particular region of a dental image is classified as carious [61]. For instance, Grad-CAM can highlight specific areas in radiographs or intraoral images that contribute most to the prediction, aiding in the precise localization of early carious lesions. This kind of interpretability builds trust among clinicians and patients, ensuring that AI is seen as an assistive tool rather than a "black box" [62, 63].

4 Conclusion

This review mainly highlights the transformative potential of AI technologies in ECC prediction and diagnosis, emphasizing models such as SVM and ANN for their robustness and adaptability. The SVM algorithm and ANN provided almost 90% of accuracies in the works of the studies. Moreover, SVM can handle high-dimensional data and resolve classification issues, and ANN can integrate variables and handle enormous amounts of data. Moreover, the performance of models might change based on the data used, the parameters involved, and the nature of the disease and its diagnosis.

However, the innovation in AI technologies associated with ML and DL would lead to drastic development in the clinical field and facilitate precision medicines, recommendations in dental examinations, and decision-making in diagnosing dental illness. In conclusion, the application of AI technologies, including ML and DL, holds significant promise in advancing the diagnosis, prognosis, prediction, and treatment of early childhood caries. By leveraging large datasets and sophisticated algorithms, dental professionals can improve patient outcomes and enhance clinical decision-making in oral healthcare. These efforts can pave the way for a new era of precision dentistry, where AI-driven diagnostics and treatment strategies enhance patient outcomes and streamline oral healthcare delivery. Future research should focus on integrating AI tools into clinical workflows to enhance their applicability in real-world dental practices. Efforts should also aim at optimizing AI models for precision medicine in dentistry, ensuring they cater to diverse and representative datasets while addressing ethical considerations such as data privacy and algorithmic bias. These advancements will support the development of lightweight and computationally efficient AI systems, further enabling precision dentistry.

Author contributions

Priyanka A: Data curation, formal analysis, methodology, validation, visualization, writing–original draft, writing - Review & Editing. Rishi Sreekumar: Data curation, formal analysis, methodology, visualization, writing–original draft, writing - Review & Editing. Namasivaya Naveen S: Data curation, formal analysis, methodology, investigation, supervision, project administration, validation, visualization, writing–original draft, writing - Review & Editing.

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Declarations

Ethical approval and consent to participate

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