Impact of Machine Learning and Prediction Models in the Diagnosis of Oral Health Conditions

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Abstract: *Introduction*: Recent developments in data science and the employment of machine learning algorithms (ML) have revolutionized health sciences in the prediction of diseases using laboratory data. Oral diseases are observed in all age groups and are estimated to affect about a 3.5billion people as per WHO 2022 statistics. Using the existing diagnostic data and taking advantage of ML and prediction models would benefit developing a prediction model for diagnosing oral diseases. Hence, it is quite essential to understand the basic terminologies used in the prediction model.

Methods: We retrieve various research papers using Scopus, PubMed, and google scholar databases, where prediction models were used in dentistry. The idea of this review is to explore current models, model validation, discrimination, calibration, and bootstrapping methods used in prediction models for oral diseases.

Results: The current advancement of ML techniques plays a significant task in the diagnosis and prognosis of oral diseases.

Conclusion: The use of prediction models using ML techniques can improve the accuracy of the treatment methods in oral health. This article aims to provide the required framework, data sets, and methodology to build ML and prediction models for oral diseases.

Keywords: Machine learning, Prediction Model, Dentistry, Model Validation.

INTRODUCTION

Oral health conditions are the most frequently observed diseases worldwide [1]. It not only affects general health but also the quality of life. With the help of ML and prediction models now it is easy to uncover disease patterns, and risk patterns and develop prediction models for oral disease. These models provide valuable insights into the stratification of risk, decision-making, and better resource utilization. Stratification of risk is one of the major applications that also observe the association between a set of predictors, which are also called risk factors, and an outcome variable for developing a clinical prediction model. Prediction models will empower physicians to predict the risk of the patient for a certain disease and diagnose accordingly.

Several clinical factors such as socioeconomic status, habits, diet, existing diseases, etc are associated with oral health conditions [2]. ML can utilize the existing data as a training data set to identify the risk factors associated with oral health conditions to give a better prediction. Observation and validation cohort, and how all these can be used to build a tool to identify.

Machine learning algorithms and predictive modeling techniques are in trend nowadays in healthcare settings [3-5]. The clinician uses these techniques very frequently to identify the risk factors and predict the disease outcome. Building multiple prediction models for the same disease is also very popular in healthcare settings [6]. It allows the researchers to compare the predictive ability of various prediction models and to choose the appropriate model for better prediction. The potential use of machine learning in oral examinations and oral cancer detection is emerging nowadays. Machine learning algorithms make it possible to swiftly and reliably analyze enormous volumes of data, which may assist with the early identification and detection of oral malignancies. The following are some applications of machine learning in oral diagnostics and oral cancer detection:

THE GOALS OF USE OF ML IN ORAL HEALTH CONDITIONS

Developing and validating dental prediction models.

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To help the clinician to improve patient care using machine learning. By examining tissue samples or biopsy samples, machine learning algorithms can be employed to help confirm the existence of oral cancer. These algorithms can identify cancer cell patterns and traits that human analysts could overlook.

Solve complex dental treatment-related problems by using evidence-based dentistry. A patient's unique traits and medical history can be taken into account when using machine learning algorithms to analyse patient data and offer personalised treatment strategies. This can lessen the chance of problems and improve treatment results.

Risk stratification and finding out the probability of risk in severe oral diseases i.e. Oral cancer. Based on a patient's demographics and medical history, machine learning algorithms can be used to estimate that patient's likelihood of acquiring oral cancer. This can aid in locating high-risk individuals who might require more regular screening and observation.

X-rays, CT scans, and MRI scans of the oral cavity can be analysed by machine learning algorithms to look for anomalies or indications of malignancy. These algorithms are capable of spotting differences and trends that could be challenging for human analysts to notice.

Overall, machine learning has the potential to significantly improve the speed and accuracy of oral cancer diagnosis, resulting in earlier detection and better patient outcomes. Machine learning algorithms, it is crucial to remember, should be used in conjunction with clinical judgment and knowledge and not as a substitute for human physicians. It can be employed in advanced and research-oriented attitude in oral health.

Model Development Using Predictors

To develop a good clinical prediction model, a lot of clinical parameters should be taken into consideration [7]. The priority in the development of the model is to identify a clinical outcome of interest and all the possible dependent variables and a set of predictors. The intervention of clinical experts is needed to define the important factors/parameters that may affect the outcome of the disease for predictor variables or potential predictors. Traditionally, statistical models use logistic regression to predict the clinical outcome. Whereas, for multiple prediction models use linear regression, decision tree, Random forest, artificial neural network, and support vector machine [8]. All these prediction models use a variety of statistical methods, and machine learning algorithms to classify the disease risk outcome. However, internal validation and external validation play a crucial role in implementing a new predictive model [9] and are explained in detail in the Model validation section. A review of the literature provides us with the use of predictors in past research (examples).

Model Validations

Model validation is a critical part of the development of any clinical prediction model [27]. In oral health also it is quite essential to check the model validity. In simple terms, model validation can be defined as the statistical performance and assessment of the prediction model. Model validation can be categorized into two parts, internal validation, and external validation.

Internal validation refers to building a prediction model and evaluating the performance of the model using the same data set [27]. This method is also called a split sample method. In the split sample method, the data set is randomly divided into a training data set and a validation data set. The training data set usually covers 80% of the entire data and is used to build a model or train the model. The remaining 20% of the data is used to test the model and is referred to as a validation data set. Usually, this method requires relatively a large sample size and variables.

The researchers observed the discrimination and calibration of the model in the test data set. It does not perform well enough; a new model needs to be proposed by the researcher. In this case, it will be called the inappropriate predictive ability of the model. External validation is also a useful aspect of model validation. This type of validation is usually done in different cohorts. for example, a researcher developed a model to predict heart disease in a particular location. To ensure the predictive ability and conduct external validation, the same model can be validated in different locations and can check the accuracy of the model.

Model Discrimination and Calibration

Model discrimination refers to the discriminatory ability of the model. Also, we can define model discrimination as the predictive ability of the model [28]. Model discrimination refers to how accurately the model can classify the risk of any particular disease. e.g. High risk or low-risk. After building the final model by selecting all the features and various machine

Table 1: Examples of Different Predictors used to Predict Outcomes in Different Study

Reference	Predictors	Outcome of interest
Harshad Hegde *et al*. [10]	Age, Bmi, Gender, Hypertension, Bleeding on probing (BOP), Family history of Diabetes, LDL cholesterol, Serum Creatinine Levels, Ethnicity	Predicting DM Risk in a dental clinical environment
Wan Muhamad *et al*. [11]	Age, Treatment, Distance metastasis	Oral Squamous Cell Survival Carcinoma
Chui S. *et al*. [12]	Sex, age, smoking history, alcohol history, HPV status EBV status, Past cancer history, Anterior tongue, Posterior tongue, Buccal mucosa, Lips, Hard palate, soft palate, Maxillary gingival, tonsil	Prediction of oral cancer
Mi Du *et al*. [13]	Patient-related-(Age,sex,Ethnicity,Race,Dental insurance,education,income) Practitioner-related-(Practitioner sex, Practitioner specialty, Practitioner ethnicity) Tooth-related-(Maxillary tooth, Tooth site)	predicting pain following root canal treatment
Shihui shen *et al*. [14]	A total of 748 panoramic images of adolescents aged 5–13, including 356 females and 392 males, were included in this study.	Dental age
Li-Chen *et al*. [15]	Age, Sex, Educational level, Marital status, Indigenous peoples, Degree of urbanization, Diabetes, Other cancers, Other catastrophic illnesses, Health-related behaviors, Monthly salary	Risk of Oral Cancer Incidence
You-Hyun eta al. [16]	Age, Sex, Children with siblings, income, Tooth brushing frequency, Education level of the mother, Use of dental floss, Brushing frequency of the mother	Early Childhood Caries
GHANIM *et al*. [17]	Age, sex, Debris Index, Age children started toothbrushing, Age at the first dental visit, Age breastfeeding stopped, Sleep with bottle and milk formula, No of soft drinks use, no of sweets consumption.	Caries prediction
Shi Huang *et al*. [18]	Features of metagenome shotgun sequences	Gingivitis severity
Lai H *et al*. [19]	Age, Gender, Education level, Brushing frequency(per day), Flossing experience, Recent dental visit, Brushing concept, Mobile tooth, Gingival bleeding, Cigarette Smoking, Betel-quid chewing, Alcohol, BMI	Periodontal disease
Shimpi *et al*. [20]	Age, sex, Medicaid status, medicare status, height, weight, BP, HDL, LDL, Triglycerides, Duration of diabetes, Frequency of tooth brushing, Frequency of tooth flossing, Oral hygiene status, Presence of dental calculus	Accessing periodontosis risk
Ozden *et al*. [21]	Gender, Education, Smoking, BOP=Bleeding on probing; RBL=Radio graphically bone loss; PI=Plaque index; GI=Gingival index; PD=Pocket depth; CAL=Clinical attachment level; GR=Gingival recession;	Diagnosis of peridentosis
Choi *et al*. [22]		Orthognathic surgery
Liu *et al*. [23]	Age, Residence area, Number of true teeth, Dental insurance, Lifestyle, Smoking, Drinking alcohol, Eating candy frequently, Domestic water access, Use of a toothpick, Use of dental floss, Use of fluoride toothpaste	Dental caries risk prediction
Hung *et al*. [24]	Demographic data and questionnaires for root caries	Identification of root caries risk
Geetha *et al*. [25]	X-ray images data	Dental caries using radiographs
Schwendicke *et al*. [26]	Radiology images data	Detecting caries lesions in near-infrared light images

learning algorithms, Researchers use internal validation or external validation method to observe model discrimination.

One of the major tools to evaluate model discrimination is the receiver operating curve (ROC). Usually, ROC analysis was traditionally done to evaluate the model discrimination. Predicted probability is evaluated by the machine learning algorithms used to plot the ROC curve [29]. The receiver operating curve is plotted by taking sensitivity and 1-specificity for every possible cutoff for the predictive probabilities. The area under the receiver operating curve (AUROC) usually explains the discrimination ability of the model.

This area can be classified into several points to access the model discrimination. If the AUROC of the model is 0.50 or less, it will be called a poor discrimination ability of the model. Similarly, an AUROC value of 0.7 to 0.79 is considered good model accuracy, if the AUROC represents between 0.80 to 0.89 it will be called a very good discrimination ability of the model [29] and finally, the AUROC greater than 0.90 indicates excellent model discrimination. Researchers usually evaluate the 95% confidence interval for each AUROC.

ROC curve analysis is also performed for finding out the optimal cutoff point for a continuous variable. For example, we may consider a risk score for dental disease derived from a model.

Role of Machine Learning in Dentistry

In studies on oral cancer, machine learning (ML) has been used extensively to investigate the distinction between well-differentiated (WD) oral squamous cell carcinoma (OSCC) and moderately or poorly differentiated OSCC [30] and to predict the likelihood of lymph node metastasis in early-stage oral tongue cancer [31, 32]. Machine learning techniques were used to categorize whether dental caries were present or not. To establish the prognosis of root caries for specific individuals, several supervised machine learning techniques were used, including logistic regression, k-nearest neighbors (k-NN), random forest regression, and extreme gradient boosting (XGBoost). It allows evidence-based, individualized dental care that could reduce root caries experiences through early prevention and care [33]. The early detection and treatment of periodontitis are made easier with the aid of machine learning. Additionally, ML acts as a link between traditional markers and immunologic and microbiological characteristics to be included in the periodontal diagnosis [34]. Working with bacterial profiles, immunological characteristics, molecular profiles, and clinical data, ML algorithms have shown good performance. For conclusive proof of the precise diagnosis of periodontal disease, the study of gene expression patterns from periodontal tissue biopsies, detection of bacteria in subgingival fluid samples, and determination of bone levels are all essential.

LR-Logistic Regression DT-Decision tree, ANN-Artificial Neural Network SVM-Support Vector Machine, KNN-K Nearest Neighbor NB-Navi Bayes XGBoost-Gradient Boosting RF-Random Forest AUC-Area Under Curve RMSE-Root Mean Square Error.

DISCUSSION

In this paper, we discussed a general overview of building prediction models using machine learning techniques for dentists and clinicians. Here, we put light on model development, model validation, and utilization of the model. While building prediction models in clinical settings, feature selection must be

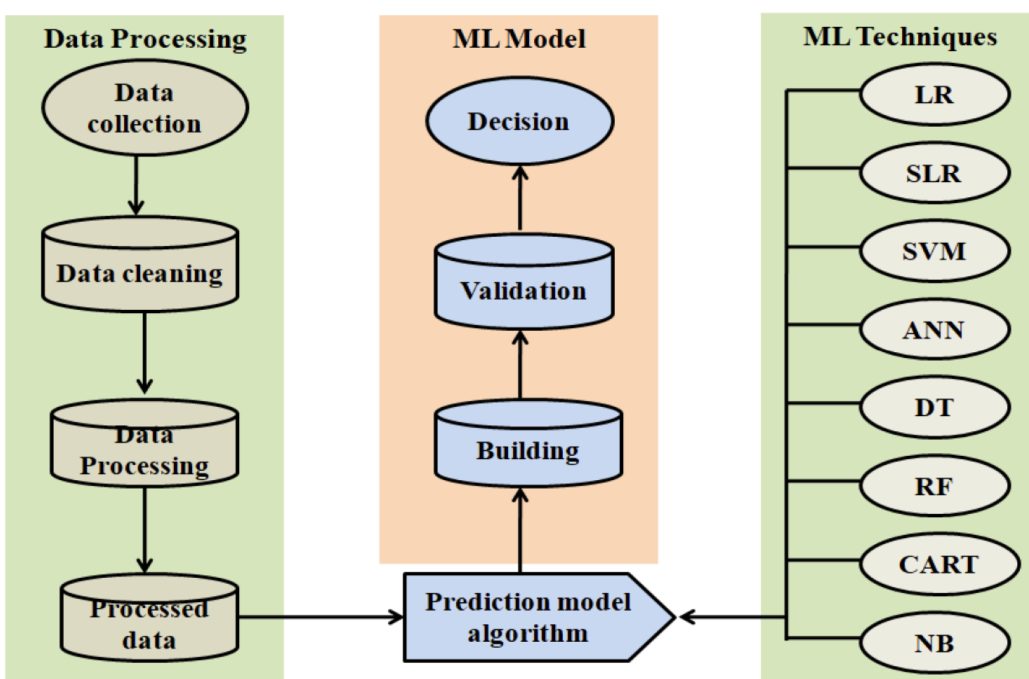

Figure 1: Road map for model development and validation.

Table 2: Illustrative Example of Different Models and their Performance in Dentistry

Reference	Oral diseases/application	Data source	ML Techniques	Accuracy
Harshad Hegde *et al*. [10]	non-invasive diabetes risk prediction from medical dental data	Clinical data	LR, MLP, RF, SVM	RF-Accuracy(0.94) Sensitivity(0.94) Specificity(0.93)
Wan Muhamad *et al*. [11]	Oral Squamous Cell Survival Carcinoma	Hospital-based data	Linear regression	R-squared (0.9014)
Chui S. *et al*. [12]	Oral Cancer	Retrospective patients data	LR, DT, SVM.KNN	DT-accuracy-(70.59) AUC-0.67
Mi Du *et al*. [13]	root canal treatment	Secondary RCT data	Multilevel logistic model	Auroc-0.85
Shihui shen *et al*. [14]	Dental age	Clinical data	DT, BRR, KNN	KNN-(ME = 0.015, MAE = 0.473, MSE = 0.340, RMSE = 0.583, R^2 = 0.94).
Li-Chen *et al*. [15]	Risk of Oral Cancer Incidence	High-risk population-based data	LR	AUC-0.73,Sensitivity-0.77,Specificity-0.56,Positive predictive value-0.63,Negative predictive value-0.71
You-Hyun *et al*. [16]	Early Childhood Caries	Data of 4195 children aged 1–5 years	RF, LR, XGBoost	
GHANIM *et al*. [17]	Caries prediction	Saudi preschool children, data	LR	Predictive probability-0.86,Sensitivity-0.90,Specificity-0.80
Shi Huang *et al*. [18]	Gingivitis severity			
Lai H *et al*. [19]	Periodontal disease	National survey data from the Taiwan survey	LR	AUC-0.72, Sensitivity-0.63, Specificity-0.68
Shimpi *et al*. [20]	Accesing peridentosis risk	Patient data	NB, LR, SVM, ANN, DT	NB-(0.80),LR-(0.78),SVM-(0.79),ANN-(0.84)-DT-(0.91)
Ozden *et al*. [21]	Diagnosis of peridentosis	Patient data	SVM, DT, ANN	SVM-(0.98),DT-(0.98),ANN-(0.46)
Choi *et al*. [22]	Orthognathic surgery	316 patients data	ANN	ANN-(0.96)
Liu *et al*. [23]	Dental caries risk prediction	Geriatric patient range from age 65-74	GRNN	AUC-0.777
Hung *et al*. [24]	Identification of root caries risk	5135 Individual data	SVM, RF, LR	SVM-(0.97),RF-(0.94),LR-(0.74)
Geetha *et al*. [25]	Dental caries using radiographs	Intra-oral digital radiography data	BPNN	BPNN-(0.971)
Schwendicke *et al*. [26]	Detecting caries lesions in near-infrared light images	Patients data	CNN	AUC-0.74(0.66-0.82)

done properly to establish a reliable and reproducible model. We discussed how internal validation and external validation play a vital role in model validation. However, internal validation is quite an easier process as compared to external validation. External validation is a rigorous process.

Internal validation deals with the re-sampling method or split sampling method where the researchers can split up their data set into two different partitions. It depends on the researchers, and how to split the data set. It may be either an 80% training set or a 20% testing set or a 70% training set and a 30% testing set. We cannot say that the model is fully validated until the external validation is done properly. External validation provides a generalizable result on how the model will perform in the future and how clinicians can use this to develop the same type of prognostic model. This validation process arises in prediction models and includes the conception of all common validity methods found in survey research, which covers face validity, concurrent validity, content validity, criterion validity, and construct validity.

In our article, we focus on how to build a prediction model in dental care settings. Most of the clinical and dental outcome deals with dichotomous variables. E.g.Dental caries (yes\no), and pre-cancer (yes, no). However, in many cases, clinicians face continuous outcomes, categorical outcomes, and time-to-event outcomes. Clinical prediction models with machine learning algorithms provide a huge advantage to deal with all types of variables.

LIMITATIONS

Although clinical prediction models are emerging research techniques nowadays, some wrong model selections and inappropriate feature selection may lead to unusual results in research. However clinical prediction models must follow clinical judgment for better accuracy.

CONCLUSION

The clinical prediction model in oral health provides many applications in clinical settings. We cannot use these models to recognize the causation of therapy efficacy; however, these models can provide the dentist and clinicians to stratify the risk score and produce suitable interventions as soon as possible. These models also help in cost and resource utilization. As we know clinical prediction models are utilized in a large clinical setting, thus it is of utmost importance to understand the underlying algorithms work behind the model to develop and validate it. Apart from basic research in oral health, clinical prediction models and machine learning algorithms enhanced the researchers and dentists to do advanced research.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

PREVIOUS PRESENTATION IN CONFERENCES

No.

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