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Optimum model for Prediction of Dental Anomaly Patterns with Deleterious Oral Habits among School Going Children-A Machine Learning Approach

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ABSTRACT:

This study is to find the association between dental anomaly patterns(DAP) with deleterious oral habits among school going children of age 07 -13 years, in National Capital Region and predicts the most informative etiological criteria to the DAP development through machine learning. Openbite, spacing and tongue thrust has positive correlation, $p<0.05$ while crowding and spacing has negative correlation with gender, p<0. 05. The nail biting in age groups 7-9, 10-11 and 12-13 years (22.7,25.and 20.3%) is highest and tongue thrust (20.5,19.6 and 22.1%) associated with these groups respectively. Open bite neural network has Accuracy, AUC and Gini are 95.0%, 0.684 and 0.368 respectively which is better than other classifiers in training data and in test sample is 94.3% accuracy. Cross bite Neural network has Accuracy, AUC and Gini are 94.8%, 0.697 and 0.394 respectively which is better than other classifiers in training data and for test sample is 94.8% accuracy. The detection and management of dental anomalies patterns in early age can avoid potential orthodontic and esthetic problems in a child.

KEY WORDS: Machine learning, deleterious oral habits, Decision tree, Neural network, Dental anomaly patterns

1. INTRODUCTION

Malocclusions are present a traceable public health problem as it has high treatment cost for the patient and leading to a pessimistic impact on quality of life. The high prevalence rate of malocclusion results aesthetic and functional impairment. A habit is a practice which is considered bad that we do repeatedly and finds it difficult to stop doing.For example, ear pulling,finger,eye rubbing nose-picking, scratching,hair twistingand oral habits. The stereotypic repetitive functions of the masticator system andits physiological suppressed differing qualitative and quantitative function were called the oral habits [1,2]. The patient operatessilently and insensiblyabnormal oral habits and unaware of the existence of them. These simple habits are performed by consciously at first time andeffort becomes less conscious with each repetition and it is strictly applicable only for motor responses. Eventually the consciousness is removed and these oral habits aredecided absolutely unconscious and became a part of the routine of the mind [1,2].

The oral habits may cause serious effect on facialgrowth and dentition of children, adolescents and adults. These bad oral habits create a condition whereteeth are departed from standard relation to the other teeth in to either the same dental arch or to the opposite arch, which causemalocclusion.These habits can shift the position of teeth out of alignment. The most common etiologies for orthodontic malocclusion in children are the oral habits [3,4].

Oral habits, if extend beyond the preschool age may cause various types of malocclusions, that in future may require orthodontic intervention. As the duration of the habit increases, the probability of a child developing a class II malocclusion also increases. If the habit was stopped early [before 6 years), the effects on occlusion were

often transitory. Oral habits, if extend beyond the preschool age may cause various types of malocclusions, that in future may require orthodontic intervention. As the duration of the habit

increases, the probability of a child developing a class II malocclusion also increases. If the habit was stopped early [before 6 years), the effects on occlusion were often transitory.

Orthodontic interventionin future may require is required if theOral habits areextended beyond the preschool age and cause various types of malocclusions.The chance of occurrence of a child developing a malocclusion increases with the increment of duration of the habit. The effects on occlusion are temporary if the habit is stopped before 6 years.The increase in intensity, duration and frequency of the deleterious oral habits (DOH) will increase the severity of the malocclusion [5,6].

According to author knowledge, ML algorithms has not been used to develop models in prediction of Malocclusion, Dental anomalies patterns (DAP) as dependent variables and demographic and deleterious oral habits as independent variables. The ML approachwas used to select the most important variables from the demographic and deleterious oral habits of persons which are responsible to develop dental anomaly patterns in a person [7,8].

This study was attempts to find the association of DAP with DOH and predict the different DAP byDOH that may assist in controlling malocclusion experience of aging populations via early prevention and treatment.

Thehabitation of DAP was detected by the guidelines of World Health Organization. The existence of DAP like mouth breathing, thumb sucking, Bruxism, lip biting, nail biting and tongue thrustwerenote down. The clinical findings for each oral habit were recorded.The children of age07–13 years were included in the study whereas Children with developmental disabilities, Intellectual Disability children, the children unable to function optimally not included in the study [6-8].

ML is the field of Artificial intelligence that uses to computer models for prediction of dependent variable with the relationship of independent variables. ML can be thought of as the next level from regression analysis in the continuum of statistics [9].

The different ML algorithms were applied to a training data set. These algorithms automatically generate rules by “learn” the patterns which are present in the data and that are used to predict future outcome from the features or variables. The performance of the predicted model is passed by comparing the predicted values with the actual values from a test data set of validation data set for examples. If the relationships between variables are not obvious and data is large and complex then machine leaning approach is very helpful.This approach is very helpful for clinical decision and it have a contribution to diagnosis and prognosis of oral health conditions of persons and personalized dental treatment regimens [4,6,8].

The purpose of this paperis to develop a high accuracy model to predict the dental abnormality pattern by possible classification ML techniques. Many ML algorithms have been used for prediction of dental abnormality pattern and different classifier has been used to calculate the accuracy of predictive models.

2. Material and Methods

This section includes a detailed description about dataset of study and ML algorithms used in this study. The knowledge about medical terms and procedures from dental doctors is required to initiate prediction process of therefore a discussion was done with few dentists for the clarity of DAP concepts and clinical data was collected by a dentist [10,11].

2.1 Problem: The high prevalence rate of malocclusions represents a relevant public health problem and it hashigh treatment cost for the patient and leading to a pessimistic impact on quality of life. The heredity and DOH are scanned as an important factor in the etiology of DAP. Therefore, it is necessary to find which oral habit mostly affect dental abnormality pattern.

2.2 Data collection:

The study has sample of 300 girls and 450 boys of school of age 07- 13 years, who were attending non-government/government schools in National Capital region (NCR), India using systematic random sampling.The prior permission from the parents was taken before the child' examination. Clinical examination was carriedout by examiners by using latex gloves, mouth mirrors and probe. The presence and the type of deleterious oral habits were detected by the guidelines of World Health Organization [12,13]. The demographic characteristics of children,existence of DAP like mouth breathing, thumb sucking,Bruxism, lip biting, nail biting and tongue thrust were recorded.Clinical findingsDAP likespacing, crowding,cross bite, open bite, and deep bite of each oral habit were recorded. Prevalence of different bad oral habits was calculated.

2.2.1 Criteria for Inclusion

- The sample has age 07-13 years

2.2.2 Criteria for Exclusion

- Children with developmental disabilities
- Intellectual Disability children
- The children unable to function optimally

2.3 Oral investigation method: The investigation wasdone in special rooms that were provided by school. The existence of these DOH was determined independently. Theobservations were taken when children were completely relaxed.The children were seated on the ordinary chair with upright position of head and theinvestigator standing in front of the children.All the data collected as stated by the basic guidelines of oral health surveys of the World Health Organization [13].

Malocclusion i.e. Dental anomalies pattern (DAP) of each one of the 750 children was investigatedaccording to the directionof L. Baume [10].The clinical examination was done with a latex glove, throwawaysimple mouth mirror, throwaway explorer, throwawaypincers, copyingpencil, medicating solution, and handy light.

2.4 Analytic approach:

All of the collected data was entered in to MS excel and was usedfor data analysis. The statistical analysis and predictive modeling of cleaned data was done by SPSS modeler and R Software. The level of significance and confidence interval were 5% and 95%. The normality of data was tested by Shapiro wilks test. The observation of all parameters was recorded two times by an investigator and the intra observer agreement was calculated and tested by Cohen's kappa test. The relation (association) between parameters was calculated by Spearman's correlation coefficient (r) and the logistic regression was used as first classification technique [14].

In this paper weanalyzed cleaned datawhich has of9750observations and 13 variables. All the variables of a case entered in one row, i.e. data was entered horizontally.DAPwas the chosen variable of interest for all classification models.

Unnecessary variables and missing data were eliminated to clean the data. The correlation coefficient between the Specific variablesDOHi.e age,tongue thrusting,thumb sucking, mouth breathing, bruxism, lip biting, nail biting and gender were calculated. This correlation was used to identify the variable which define the DAP of the child. The cleaned datasetwas used to create training (80%) and testing (20%) subsets. The cleaned data was analyzed using KNN, decision tree, logistic regression,Naive Bayes, random forest, and Chi-square automatic interaction detection (CHAID) technique. All models were used to make predictions about the children would develop DAP and all models were evaluated for its accuracy.

3. RESULTS:

Intra-examiner agreement assessed by Kappa statistic was found to be 0.88 and 0.87 for prevalence of malocclusion and deleterious oral habits, respectively. It showed a strong agreement in the observation of investigator.

The results showed the %frequency distribution of children by their age groups, 07-9 years, 10-11 years and 12-13 years was 30.5%, 32.0% and 37.5% respectively. The males(60%) and females (40%) were included in present study. The frequency distribution (%) of bad oral habits of childrenon the basisof their gender, (90%) male and (76%) female have bad oral habits.The male has more percent ofnail-biting habits (22.7%) and percent with Tung thrust habits (20.5%)and morepercent of female with nail biting habits (25.08%) and percent with Tung thrust habits (19.6%).It was found that nail biting of DOHwas the highest in all three age groups 7-9 years, 10-11 years and 12-13 years (22.7%,25.8% and 20.3%) and percentage in both age groups 7-9 years, 10-11 years and 12-13 years associated with tongue thrust (20.5%,19.6% and 22.1%) respectively.

By Spearman's correlation, Nail biting has positive and gender has negative, high significant correlation with crowding, $p<0.01$. Therefore, the crowding is more significantly present in the male children who have nail biting habit than others. Tongue thrusting habit has positive while Mouth breath habit,gender has negative correlation with spacing, $p < 0.01$ Therefore the spacing is more significantly present in the male children who have tongue thrust and without mouth breath habit than others. Tongue thrust and mouth breathe habit have significant positive correlation with open bite, $p<0.05$, which showed that the children who have tongue thrust and mouth breath have open bite than other children. The thumb sucking habit has highly significantpositive correlation with cross bite, $p< 0.01$. Age has no significant correlation with the Dental anomalies' patterns.The correlation coefficient (r) was created to determine and display the correlation between the variables in Table 1

The logistic regression was used as first classification technique. The effects of habits on individual DAP were analyzed in detail and all DOHwere entered into separate regression models for each dental anomalies pattern. Results revealed that crowding significantly affected by the nail biting habit (*P*=0.001,OR= 1.959, 95% C.I=1.302 to 2.948),bruxism habit (*P*=0.015,OR= 2.396, 95% C.I=1.187 to 4.838) and gender(*P*=0.000,OR= .468, 95% C.I=.316 to .695), Tonguethrustinghabit(*P*=0.001,OR= 2.043, 95% C.I=1.1347 to 3.098) and gender (*P*=0.001,OR= .507, 95% C.I=.343 to .749) was significantly associated with spacing. The open bite significantly affected by tongue thrust habit (*P*=0.001, OR= 2.385, 95% C.I=1.457 to 3.903),thumb suck habit (*P*=0.033,OR= 1.804, 95% C.I=1.050

to 3.101).Thumb suckers(*P*=0.000,OR= 4.913, 95% C.I=3.003 to 8.038) and nail biting habit (*P*=0.035,OR= 1.740, 95% C.I=1.038 to 2.914) significantly affected cross bite. The deep biting in children was not significantly affected by any DOH.

The clean data set included randomly chosen observations for training (80%) and testing (20%) was analyzed and developed another model by decision tree with CHAID classification techniques. All DOH were entered as input variables into separate CHAID models for each dental anomalies patternas target variables. The predicted model was verified by 4- Fold cross validation.

From Table 2,The logistic regression classification for training and test data has more than 90% accuracy for each dental anomalies pattern which is maximum for deep bite 96.6%, the area under curve (AUC) was more than 0.600 for each dental anomalies pattern which is maximum for 0.686 for cross bite and the Gini was more than zero which is maximum 0.640 for deep bite in training data.
For training data, on prediction of crowding anomaly pattern by different classification ML algorithms with children age, gender and deleterious oral habits and the Accuracy % for Neural network 87.9%, AUC .629 and Gini 0.259 is better than CHIAD, KNN after the logistic regression, which is for test sample 87.9% accuracy.
For classification of Spacing dental anomaly pattern CHAID has Accuracy%, AUC and Gini index are 88.9%, 0.64 and 0.279 respectively which is better than other classifiers in training sample and for test sample which is with 88.9% accuracy. For Open bite Neural network has Accuracy%, AUC and Gini are 95.0%, 0.684 and 0.368 respectively which is better than other classifiers in training dataand for test sample which is with 94.3% accuracy.
For Cross bite Neural network has Accuracy%, AUC and Gini are 94.8%, 0.697 and 0.394 respectively which is better than other classifiers in training dataand for test sample which is with 94.8% accuracy. The deep bite anomaly pattern classify by CHAIDML algorithm with has Accuracy, AUC and Gini are 92.2%, 0.561 and 0.123 % respectively which is better than other classifiers in training data and for test sample which is with 92.2% accuracy.

4. DISCUSSION:

There is the association of dental anomaly patterns with deleterious oral habits among school going children from 7 to 13 years old and dental anomaly patterns found45% of the presence of the deleterious oral habits. The present study showsdeleterious oral habits the thumb suck, mouth breath and nail biting occurred in the age group 10-11 years while tongue thrust, nail biting was mostly found in the age 12-13 years.

The incidence of malocclusion in children with DOH and without DOH was 74.0%, and 25.1% respectively [14].From the existing studythe occurrence of DOH is higher in male than female[15], and in other study female have more oral DOH than male[16]. The result of our study showsthat the deleterious oral habits like thumb suck, mouth breath, lip biting and nail biting are higher in girls than boys while tongue thrust, bruxism is higher in boys than girls.The nail biting was mostly found in the children than otherDOHs [17,18].

All types of DOH associated with dental anomaly patterns,the malocclusion severity related to nail biting changes with the change in intensity, duration, and frequency of deleterious oral habit

[17], present study show Nail biting has significant effect on crowding & cross bite. From the decision tree the nail biter boyshave crowding while the more girls who are tongue thrusting have crowding in training and testing data, Fig 1. The tongue thrusting relatedto the Anterior open bite. When tongue is thrust between upper and lower teeth each time the patient swallows producing open bite some time the patient allow tongue to rest in open bite space preventing the bite from closing [19].Tongue thrust is the primary factor in developing the open bite thereforethe anterior open bite mostly seen in children having tongue thrust [20]. In present study the tongue thrusting has significant effecton spacing, the tongue thrusting, mouth breathing and thumb sucking has significant effect on open bitethis agree with [20,21].The nail biters girls and tongue thrusters' boys have significantly spacing anomaly patternin training and testing data, Fig 2, and the tongue thrusters without mouth breath children have open bite pattern in training and testing data, Fig.3.Present study shows thumb sucking associated with cross bite and open bitewhich is similar as Posterior cross bite with mouth breathing, andopen bite with mouth breathing this finding agree with [22-25]. Theboys without thumb sucking are more cross bite pattern than girlsin training and testing data, Fig. 5, and thumb sucking children have deep bite patternin training and testing data, Fig. 4.

The association between deleterious oral habits and DAP in most of study was done by Pearson's chi square test and prediction of DAP was done by logistic regression. According to authors knowledge there is no literature available to predict dental anomaly patterns as dependent variable and deleterious oral habits, age and gender as independent variable through ML algorithms. Our study demonstrated significant potential of ML approaches to predict dental anomaly patterns in children due to their age, gender and different deleterious oral habits. The traditional logistic regression model has two advantages on ML that is easy to use and easy to interpreted[26]. After the overcoming the complexity of ML algorithm, these are good in prediction algorithms.
The prediction of crowding, dental anomaly pattern by neural network was better than KNN, CHAID with high accuracy, Gini index and area under then curve. On predictive modeling of Spacing, the CHAID algorithm was better predictor with more than 85% accuracy and more than 60% area under the curve (AUC). The CHAID algorithm has also more than 90% accuracy, with AUC more than 55% than other classifiers for prediction of deep bite pattern [27]. The prediction of open bite anomaly pattern by Neural network with highest accuracy 95% and AUC 68.4% was the best prediction model than developed open bite pattern by anotherML algorithm. The cross-bite anomaly pattern was predicted by neural network with more than 90% accuracy and 69.7% area under the curve.

5. CONCLUSION:

All the deleterious oral habits have significant association with dental anomaly pattern. The girls have more dental anomaly pattern than boys. The nail biting significantly positively correlated with crowding in children and tongue thrusting correlated with the open bite and spacing. Thumb sucking was also another deleterious oral habit which was correlated with cross bite anomaly pattern.The neural network predicting model has high accuracy, AUC and with better Gini index than KNN and

CHAID after logistic regression for prediction of crowding, open bite and cross bite dental anomaly pattern. The detection and management of dental anomalies patterns in early age can avoid potential orthodontic and esthetic problems in a child. This prediction will be helpful for prevention of orthodontic treatment in children.

6. DECLARATIONS

6.1 Funding: Nil

6.2 Conflict of interest/Competing interest: not applicable

6.3 Author's Contribution: All authors contributed to the study conception and design. Material preparation, data collection were performed by Manoj Kumar Sharma, Neelam Singh and Vaseem Ismail. Prediction modelling through machine learning algorithms was done by Manoj Kumar Sahrma. Vaseem Ismail done statistical analysis of the data and as Neelam Sing have pharmaceutical background she was also help to define characteristics of asthma and factors to predict asthma. Sadish Kumar Shanmugam gave overall guidance for this article.The first draft of the manuscript was written by Manoj Kumar Sharma and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

6.4 Ethics approval: not applicable

6.5 Consent to participants: not applicable

6.6 Consent for publication: No objection to publish this article in this journal.

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8. BIBLIOGRAPHY NOTES

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   His research thirst on Marine algae is widely noted. He has published 2 books, 40+ research articles, guided over 30 Research projects in Marine and other natural products. He has visited various universities & presented at conferences in **South Korea, USA, Germany, Egypt, Japan & China**. Recently he delivered 2 Keynote speeches on Marine algal drugs at **Melbourne-Australia**.
   He is a member of various professional bodies including Royal Society of Chemistry (RSC), UK. His biography has been cited in Marquis Who’s Who in Medicine & Healthcare, US. He was recognized as an Organizing Committee Member for 15th Asia-Pacific Pharma Congress, Australia, selected and commemorated for International Einstein Award for Scientific achievement, International Health Professional of the year to mention a few.

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FIGURES AND TABLES :

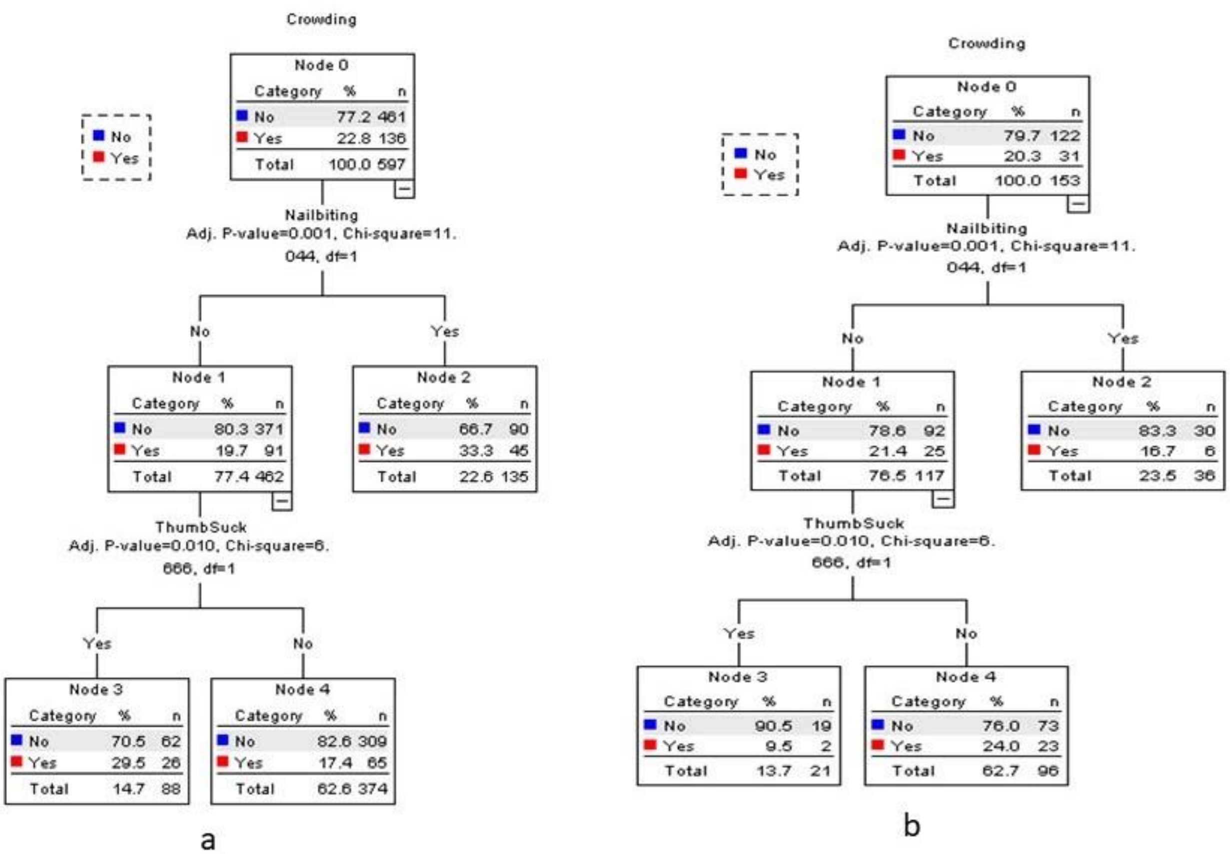

Fig. 1 Decision tree classifier for Crowding (a) For training data(b) For test data

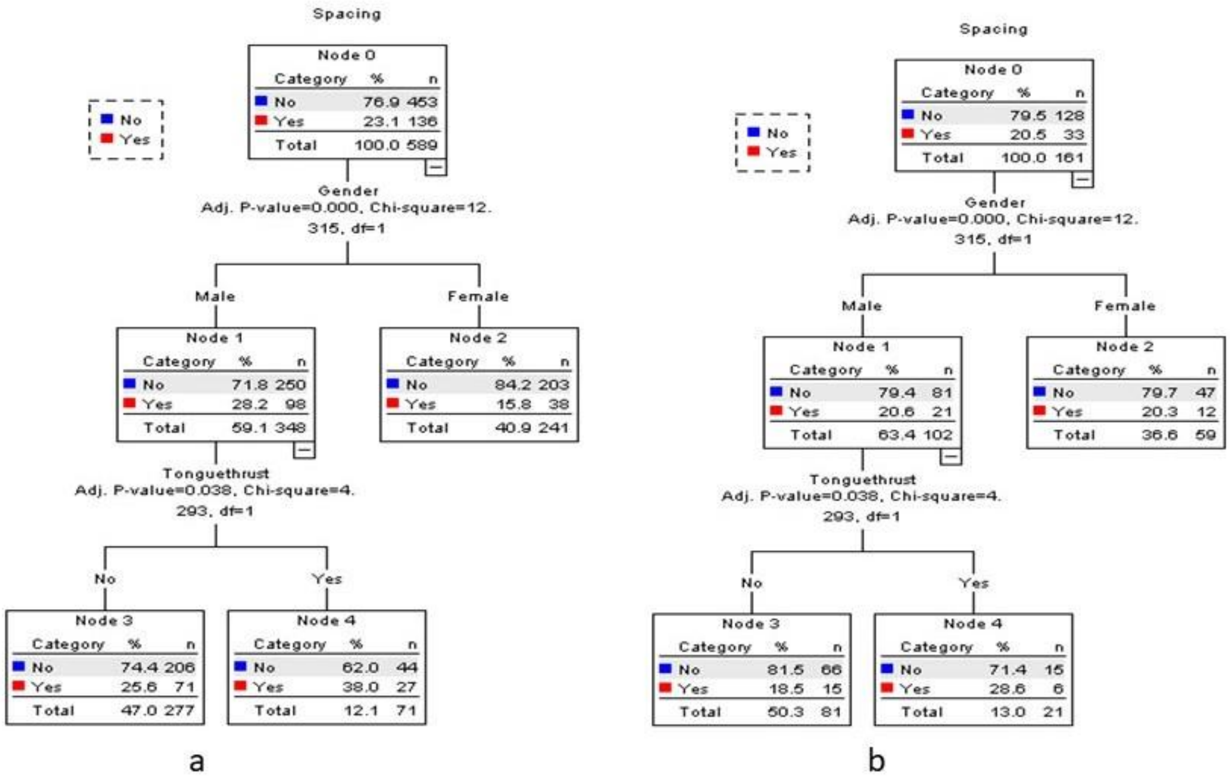

Fig. 2: Decision tree classifier for spacing (a) For training data (b) For test data

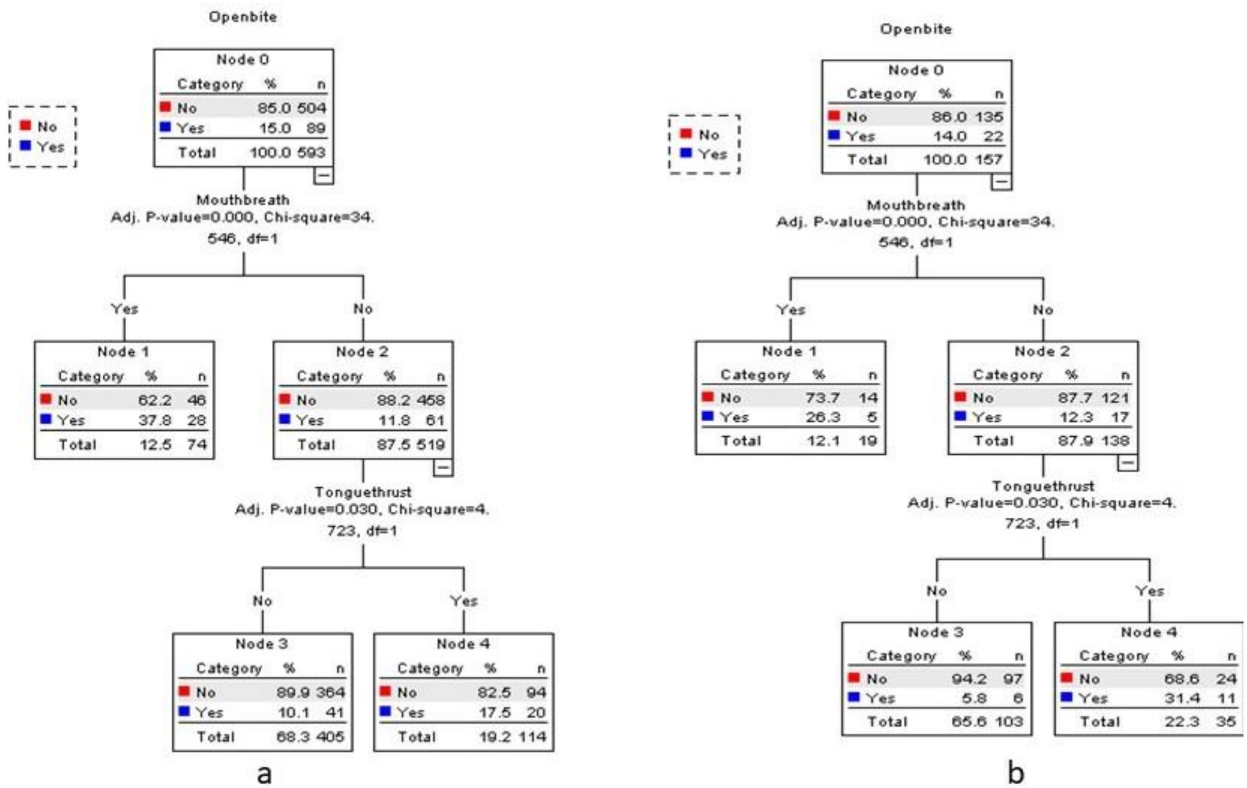

Fig. 3: Decision tree classifier for Open bite (a) For training data (b) For test data

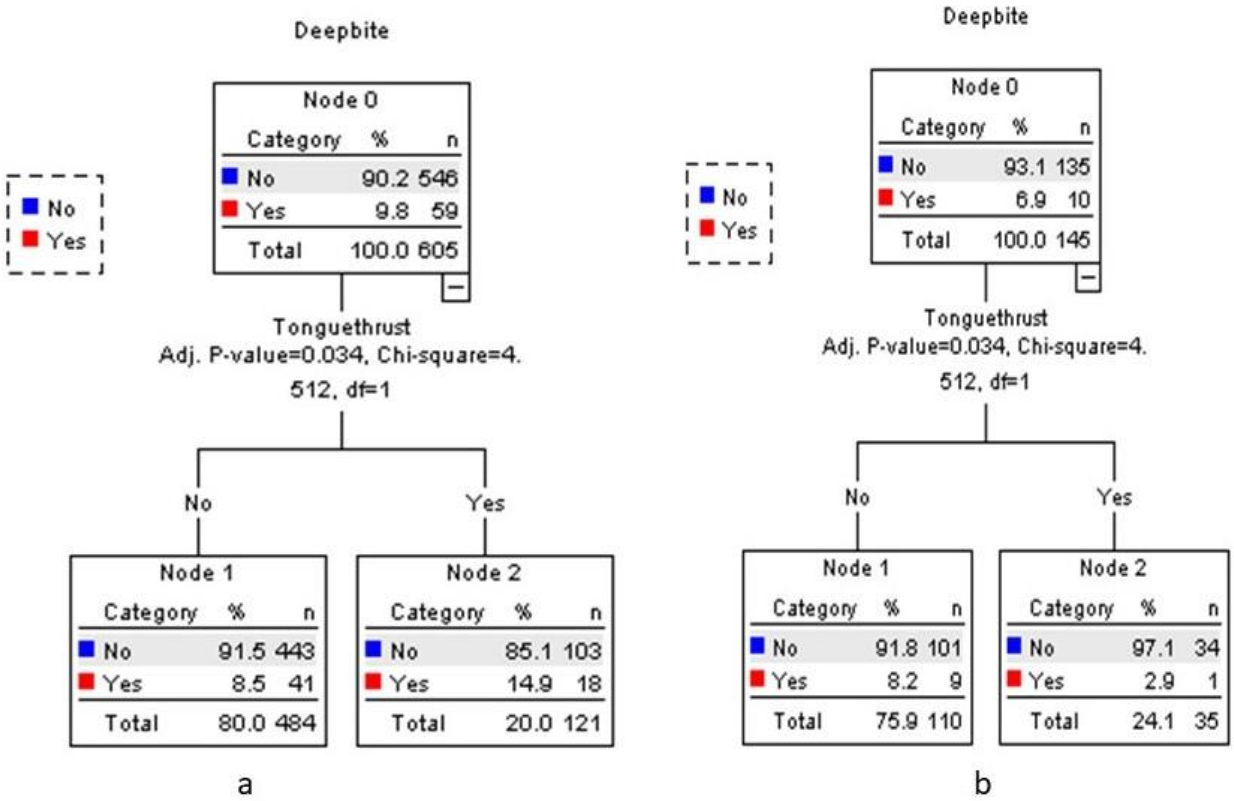

Fig. 4: Decision tree classifier for Deep bite (a) For training data(b) For test data

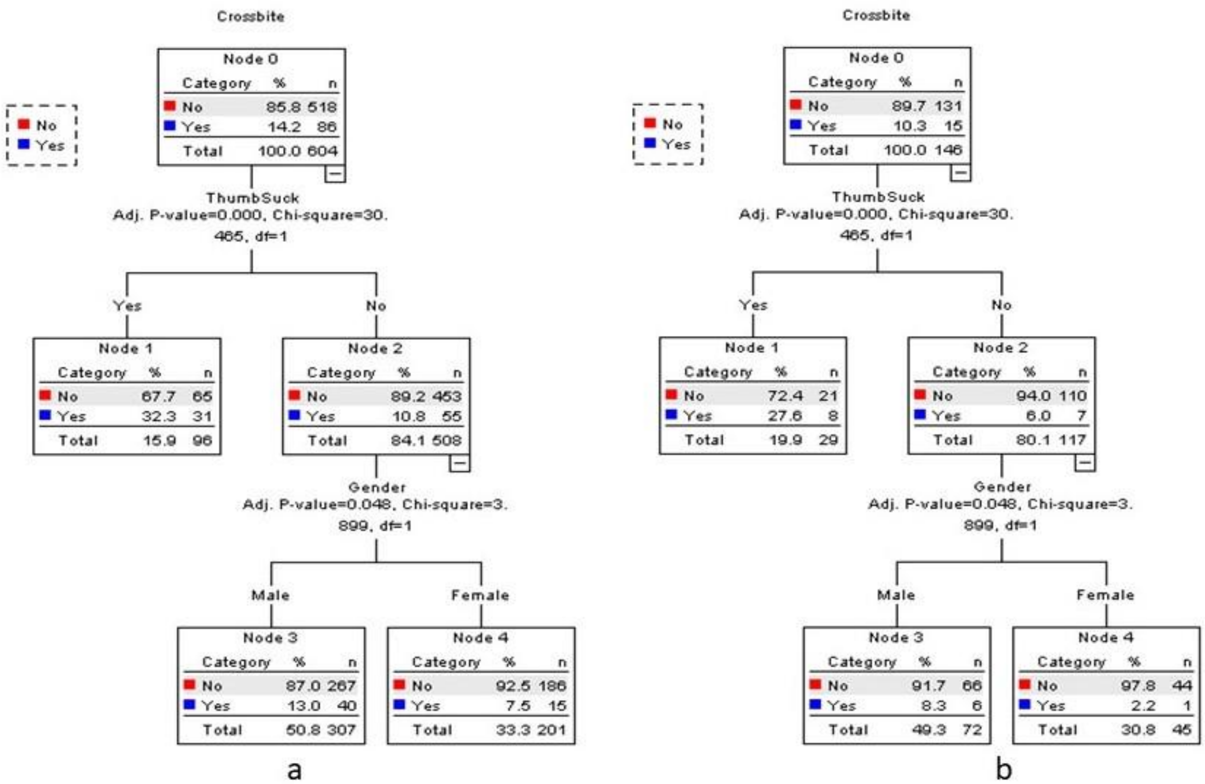

Fig. 5: Decision tree classifier for Cross bite (a) For training data (b) For test data

Table 1: Spearman's rank correlation coefficient (r) between demographic characteristics, DOH with DAP of children

Anomaly pattern	Statistics	Age	Thumb Suck	Tongue thrust	Mouth breath	Bruxism	Lip biting	Nail biting	Gender

Crowding	Correlation Coefficient	0.016	0.010	0.018	0.003	0.057	-0.023	0.099**	-0.116**
	P value	0.668	0.784	0.625	0.938	0.117	0.526	0.007	0.001
Spacing	Correlation Coefficient	0.020	0.016	0.109**	-0.077*	0.015	0.063	0.042	-0.115**
	P value	0.583	0.668	0.003	0.035	0.687	0.086	0.255	0.002
Openbite	Correlation Coefficient	0.003	0.045	0.092*	0.219**	0.024	-0.021	-0.065	0.066
	P value	0.936	0.215	0.012	0.000	0.516	0.565	0.073	0.071
Crossbite	Correlation Coefficient	-0.028	0.232**	0.010	-0.006	0.018	-0.016	0.037	-0.003
	P value	0.446	0.000	0.794	0.865	0.625	0.659	0.312	0.931
Deep bite	Correlation Coefficient	-0.028	0.043	0.053	-0.036	0.019	0.018	0.003	-0.043
	P value	0.449	0.236	0.148	0.328	0.609	0.619	0.936	0.236

*Significant $p<0.05$, ** Highly significant $p<0.001$

Table 2 : The Accuracy %, Area under the Curve AUC & Gini results foreach dental anomalies pattern of different classifiers

Method	**Crowding**	**Spacing**	**Open bite**	**Cross bite**	**Deep bite**

KNN	Acc%	AUC	Gini	Acc.%	AUC	Gini	Acc.%	AUC	Gini	Acc.%	AUC	Gini	Acc.%	AUC	Gini
Training data	83.3	0.644	0.289	83.3	0.721	0.422	83.3	0.732	0.465	83.3	0.727	0.727	83.3	0.715	0.43
Test data	83.3	0.544	0.088	83.3	0.544	0.087	83.3	0.557	0.114	83.3	0.486	0.486	83.3	0.464	-0.072
Logistic regression															
Training data	90.2	0.638	0.277	92.6	0.659	0.319	94.7	0.713	0.427	94.5	0.686	0.372	96.2	0.64	0.64
Test data	90.2	0.553	0.106	85.5	0.54	0.081	94.7	0.571	0.141	84.5	0.578	0.156	97.2	0.409	0.409
Neural network															
Training data	87.9	0.629	0.259	86.4	0.665	0.329	95	0.684	0.368	94.8	0.697	0.394	83.3	0.715	0.43
Test data	87.9	0.594	0.188	82.4	0.515	0.031	94.3	0.57	0.139	94.8	0.49	-1.19	83.3	0.464	-0.072
CHAID															
Training data	85.5	0.581	0.161	88.9	0.64	0.279	90.6	0.683	0.365	90.9	0.66	0.66	92.2	0.561	0.123
Test data	85.5	0.517	0.034	88.9	0.51	0.019	90.6	0.625	0.251	90.9	0.534	0.534	92.2	0.449	-012

Table 3: Confusion matrix of each dental anomalies pattern for decision tree with CHAID classification model and validation of model by 4-Fold cross validation

Training data	**Predicted**									
	Crowding		**Spacing**		**Open bite**		**Cross bite**		**Deep bite**	
Observed	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No	461	0	453	0	504	0	518	0	546	0
Yes	136	0	136	0	89	0	86	0	59	0
Test data No	122	0	128	0	135	0	131	0	135	0
Yes	31	0	33	0	22	0	15	0	10	0

Table 4: Confusion matrix of each dental anomalies pattern for KNN prediction model and validation of model by 4-Fold cross validation

Training data	**Predicted**									
	Crowding		**Spacing**		**Open bite**		**Cross bite**		**Deep bite**	
Observed	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No	451	18	432	24	502	0	515	1	541	0
Yes	108	18	113	26	88	5	72	7	53	1
Test data No	109	5	111	14	137	0	133	0	139	1
Yes	39	2	27	3	18	0	22	0	15	0

Table 5: Confusion matrix of each dental anomalies pattern for Logistic regression classification model and validation of model by 4-Fold cross validation

Training data	**Predicted**									
	Crowding		**Spacing**		**Open bite**		**Cross bite**		**Deep bite**	
Observed	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No	467	2	454	2	500	2	516	0	541	0
Yes	125	1	137	2	86	7	77	2	54	0
Test data No	114	0	124	1	132	5	133	0	140	0
Yes	40	1	30	0	18	0	22	0	15	0

Table 6: Confusion matrix of each dental anomalies pattern for Neural network prediction model and validation of model by 4-Fold cross validation

Training data	**Predicted**									
	Crowding		**Spacing**		**Open bite**		**Cross bite**		**Deep bite**	
Observed	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No	469	0	454	2	500	2	516	0	541	0
Yes	126	0	138	1	91	2	78	1	53	1
Test data No	114	0	125	0	137	0	133	0	139	1
Yes	41	0	3	0	18	0	22	0	15	0

Table 7: Confusion matrix of each dental anomalies pattern for CHAID prediction model and validation of model by 4-Fold cross validation

Trainin	**Predicted**

g data	Crowding		Spacing		Open bite		Cross bite		Deep bite	
Observed	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No	469	0	454	2	501	1	516	0	541	0
Yes	126	0	135	4	88	5	79	0	54	0
Test data No	114	0	124	0	135	2	133	0	140	0
Yes	41	0	30	1	18		22	0	15	0

Oral Examination :
Questionnaire:

The Performa for data collection was filled by investigator as shown below:

Title: ***DeleteriousOral habits, prevalence & effects on occlusion among the population 7 -13 years oldboys and girls school children in National capital region (NCR), India.***

Name: **Father's name:**

Mother's name: **Date:**

Sex: M☐	☐ALE	
AGE:07 - 09 YEAR ☐	10 - 11 YEAR ☐	12 - 13 YEAR ☐

ORAL HABITS	PRESENT	ABSENT
1) Mouth breathing		
2) Thumb Sucking		
3) Nail biting		
4) Lip biting		
5) Tongue thrusting		
6) Bruxism		

DENTAL ANOMALIES PATTERN ASSOCIATED WITH DELETERIOUS ORAL HABITS		
1. Crowding		
2. Spacing		
3. Openbite		
4. Crossbite		
5. Deep bite		