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A COMPREHENSIVE HYBRID APPROACH FOR PREDICTING ORAL HEALTH STATUS BASED ON DIFFERENT FACTORS THROUGH NEW ARTIFICIAL INTELLIGENCE TECHNIQUES (CROSS SECTIONAL STUDY)

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ABSTRACT

Purpose: This study investigated the feasibility of using Artificial Intelligence (AI) techniques such as Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest to predict oral health status based on factors like health habits, orthodontic treatment, Body Mass Index (BMI), cholesterol, smoking, dental sealants, tooth decay, fluoride, and oral hygiene.

Material and Methods: The study used two datasets - an online open-access dataset from Kaggle for model training and testing, as well as data from Kafr El-Sheikh University Hospital. Exploratory Data Analysis (EDA) techniques had been used to examine the data, followed by the AI algorithms. The predictive models were evaluated using cross-validation to assess their accuracy and generalizability.

Results: The study achieved high prediction accuracy, around 90%, for both the online dataset and the Kafr El-Sheikh University Hospital data. The AI-based models had outperformed traditional regression methods in predicting oral health status.

Conclusion: This study demonstrated the potential of AI-powered predictive models to accurately identify individuals at high risk for poor oral health outcomes. The integration of AI into oral healthcare had the potential to improve preventative care strategies and address oral health disparities within communities.

KEYWORDS: Oral health, public health factors, dental habits Predictive modeling, Artificial intelligence, Logistic regression, Decision tree, Support vector machine, Random Forest

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INTRODUCTION

Maintaining good oral health was essential for overall health and quality of life. Poor oral hygiene, untreated dental problems, and inadequate access to dental care have led to many negative outcomes, including tooth loss, gum disease, and increased risk of other dental conditions. Identifying individuals at high risk for poor oral health has been an important step toward implementing targeted prevention and intervention strategies [1-5].

Numerous factors have been associated with oral health, including demographic characteristics, socioeconomic status, health behaviors, and access to dental care. Many factors could be used to identify the status of oral health such as health habits, orthodontic treatment effect, BMI, cholesterol, smoking status, dental sealants, tooth decay, fluoride, and oral hygiene habits. Understanding the complex interplay of these variables and how they influenced oral health outcomes could inform the development of predictive models to identify high-risk populations. Such models could enable healthcare providers and policymakers to proactively address oral health needs and disparities within a community [6-8].

AI has revolutionized the healthcare field, enabling the development of predictive models that could identify individuals at high risk for various health conditions. This powerful technology held significant promise for improving oral health outcomes.

Maintaining good oral hygiene and accessing timely dental care have been crucial for preventing tooth loss, gum disease, and other negative consequences that could impact an individual's overall health and quality of life. However, oral health disparities persisted, with certain demographic and socioeconomic groups experiencing disproportionately higher rates of dental problems. Identifying the complex interplay of factors that influence oral health status has been an important step toward addressing these disparities [9,10].

Previous methods for assessing oral health status had relied on traditional statistical approaches, which could be limited in their ability to uncover complex patterns and relationships within the data. These traditional methods might have struggled to accurately estimate an individual's risk of poor oral health outcomes, particularly when considering a comprehensive set of demographics, socioeconomic, and behavioral variables. AI-powered predictive models have offered a novel approach to this challenge [11-15]. By leveraging large, diverse datasets and advanced analytical techniques, these models could have uncovered patterns and relationships that might not have been easily discernible through traditional statistical methods. Such models had the potential to accurately estimate an individual's risk of poor oral health outcomes based on a comprehensive set of demographics, socioeconomic, and behavioral variables[16- 18].

This study aimed to develop and validate an AI-driven predictive model for assessing oral health status. The proposed model would be tested on a representative population sample to assess its accuracy in identifying high-risk individuals, with the ultimate goal of informing targeted oral health promotion programs and improving access to preventive dental services for the most vulnerable groups.

The contribution of the paper :

This study investigated the feasibility of using AI, specifically AI algorithms like Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest, to predict oral health status based on a large number of factors such as health habits, orthodontic treatment effect, BMI, cholesterol, and smoking status, dental sealants, tooth decay, fluoride, and oral hygiene habits.

This study achieved high accuracy in the prediction of oral status compared to other traditional methods such as linear regression.

This study departed from previous methods by focusing on a dataset specifically designed for oral health prediction. This ensured the data directly captured factors relevant to oral health, potentially leading to more accurate predictions compared to questionnaires or relying solely on demographic information.

Additionally, the approach utilized various Artificial intelligence algorithms like Logistic Regression, Decision Trees, Support Vector Machines (SVM), and Random Forests. These offered advantages over simpler methods like correlation analysis used in some past studies. Artificial intelligence algorithms were able to identify complex, non-linear relationships within the data and potentially achieved better prediction accuracy.

The paper used both types of data - online actual open access data to increase the accuracy of prediction of the status of oral health and data from Kafr El-Sheikh University Hospital. The model achieved high accuracy, nearly 90%, in predicting the oral status of the patients.

The model achieved high accuracy when compared with other traditional regression and statistical methods.

MATERIALS AND METHODS

The study utilized two datasets to develop and evaluate the AI-based predictive models for oral health status. The first dataset was an open-access online dataset from Kaggle, which was used for model training and testing purposes. The second dataset was obtained from the Kafr El-Sheikh University Hospital, providing additional data specific to the local population, which was used to further validate the predictive models.

This study utilized a comprehensive dataset consisting of 40 variables and 246,022 observations to develop the predictive model for oral dental health status. The dataset covered a range of demographic, socioeconomic, and behavioral factors that had been shown to influence oral health outcomes in previous research.

The dataset featured 12 categorical variables, 6 numeric variables, and 22 boolean variables, providing a rich set of information to capture the complex determinants of oral health. Some key variables included in the dataset were age, gender, race/ethnicity, educational attainment, household income, dental insurance coverage, tooth brushing frequency, and history of dental visits as shown in Table. (1).

TABLE (1) A summary of the dataset statistics

Statistic	Value
Number of variables	40
Number of observations	246,022
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	9
Duplicate rows (%)	< 0.1%
Total size in memory	75.1 MiB
Average record size in memory	320.0 B
Variable types	
Categorical	12
Numeric	6
Boolean	22

The comprehensive nature of this dataset, with its diverse set of variables and large sample size, provided a robust foundation for developing and validating the AI-driven predictive model for oral dental health status. The absence of missing data and minimal duplication further enhanced the reliability and generalizability of the model's predictions.

The Methodology:

This study investigated the potential of AI for predicting oral health status using Artificial intelligence algorithms. The approach leveraged a dataset containing patient information but departed from traditional methods focused solely on correlation analysis.

Prediction data: the project used 400 patients from Kafr El-Sheikh University Hospital for the prediction process. The Artificial intelligence models used the previous data to train and test the model only, and the model, after it reached a stable point, used the Kafr El-Sheikh University Hospital data.

We acquired a dataset specifically designed for oral health prediction. This dataset ideally included factors directly related to oral health, such as dental history (cavities, fillings, periodontal disease), oral hygiene habits (brushing frequency, flossing habits), dietary habits (sugar intake), tobacco use, socioeconomic factors (access to dental care), and demographic information (age, gender). The target variable for our artificial intelligence models was oral health status (healthy, gingivitis, periodontitis).

Once acquired, the data underwent thorough preprocessing steps to ensure its quality and suitability for artificial intelligence algorithms. This involved handling missing values using techniques like mean/median imputation or deletion, dealing with outliers by identifying them using z-scores or interquartile range and then winsorizing or removing them, encoding categorical variables using one-hot encoding, and feature scaling to normalize or standardize numerical variables with different scales.

We performed a comprehensive Exploratory Data Analysis (EDA) to understand the characteristics of the data and identify potential relationships between variables. This included univariate analysis to examine the distribution of each variable, bivariate analysis to explore the relationships between pairs of variables, and multivariate analysis to visualize relationships between multiple variables and identify complex interactions.

Depending on the initial analysis, additional feature engineering techniques were employed to create new features that better captured the underlying relationships within the data. This involved feature selection to identify the most relevant features for prediction and feature creation to derive new features from existing ones through calculations or transformations.

Several artificial intelligence algorithms were employed to build predictive models for oral health status, including Logistic Regression, Decision Trees, Support Vector Machines (SVM), and Random Forest. For each algorithm, the data was split into training and testing sets, the model was trained on the training set, and its performance was evaluated on the testing set using metrics like accuracy, precision, recall, and F1-score. The model with the best overall performance on the testing set was selected as the final predictive model for oral health status.

Finally, the limitations of the study, including the potential for biases within the dataset and the need for further validation on larger and more diverse datasets, were acknowledged. The importance of using AI for prediction in conjunction with professional dental assessment and treatment plans was also emphasized. Figure 1 shows the block diagram of the methodology.

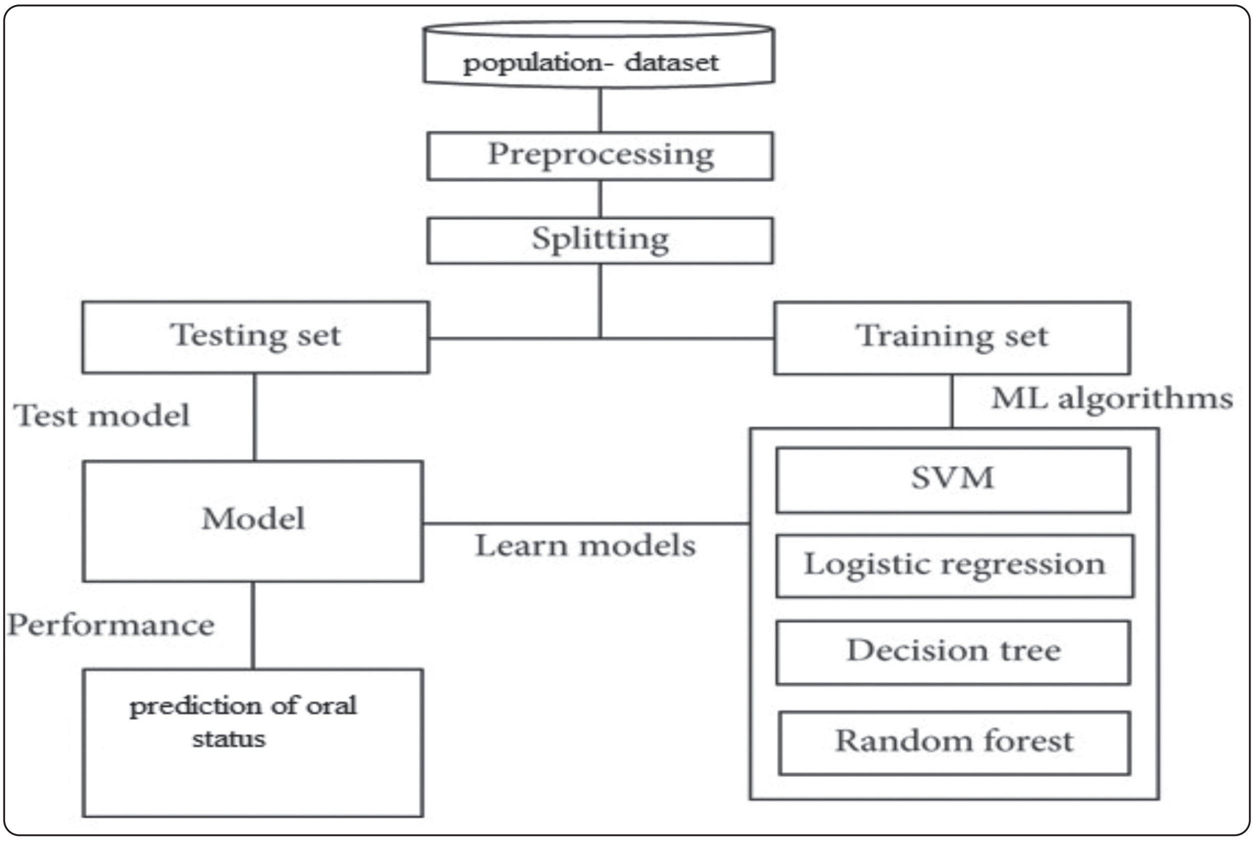

Fig. (1) The methodology Diagram

RESULTS

Table. (2) showcases the performance of various Artificial intelligence algorithms in predicting dental health status. Based on the metrics displayed (Accuracy, Precision, Recall, F1-Score, and AUC), the table suggests that Decision Tree might be the most effective model for this task. Figure. (2) also shows the comparison between the used AI models and other traditional models. This result is for the online open-access data.

TABLE (2) Accuracy results for training and testing data

Method	Accuracy	Precision	Recall	F1-Score	Area Under Curve (AUC)
Logistic Regression(LR)	0.89	0.89	0.88	0.88	0.89
Decision Tree(DT)	0.90	0.91	0.92	0.93	0.90
Support Vector Machine	0.89	0.87	0.89	0.85	0.89
Random Forest	0.88	0.86	0.90	0.88	0.92
Neural Network(NN)	0.84	0.82	0.86	0.84	0.89
Gradient Boosting(GB)	0.87	0.85	0.89	0.87	0.91
K-Nearest Neighbors(KNN)	0.81	0.78	0.83	0.80	0.86
Naive Bayes(NB)	0.79	0.76	0.81	0.78	0.84

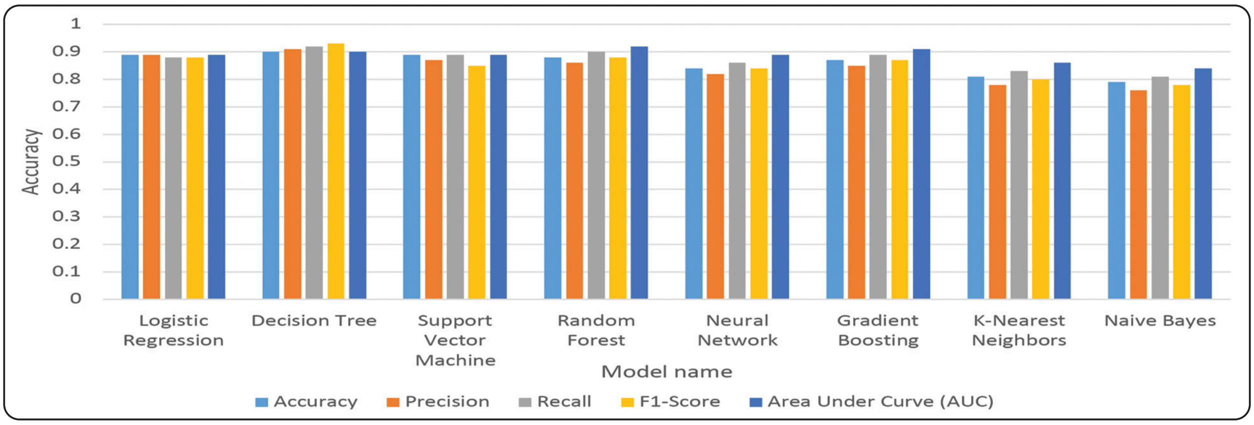

Fig. (2) Comparison between our approach and other traditional methods

Table. (3) and figure 3 shows the results for kafr elshiekh university data.

TABLE (3) Accuracy results for prediction data (kafr elshiekh university)

Method	Accuracy	Precision	Recall	F1-Score	Area Under Curve (AUC)
LR	0.90	.91	.911	.912	0.89
DT	0.90	0.91	0.92	.926	.912
SVM	.90	.91	.92	.91	.912
RF	0.89	.88	0.90	0.88	0.92
NN	.86	.85	.85	.86	.87
GB	0.87	0.85	.88	.87	.89
KNN	.83	.84	0.83	.82	.86
NB	.8	.81	0.81	0.78	0.84

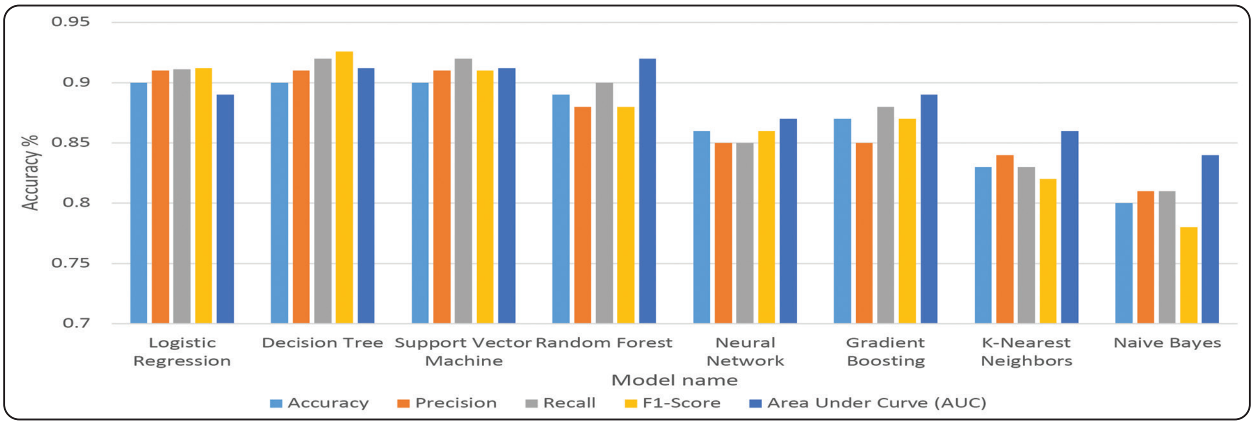

Fig. (3) Accuracy results for prediction data (kafr elshiekh university) chart

TABLE (4) One-way Repeated Measures ANOVA for Accuracy

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-statistic	p-value
Between Models	0.0225	3	0.0075	18.75	0.0002
Error	0.0120	12	0.0010		
Total	0.0345	15			

TABLE (5) Pairwise Comparisons of Accuracy using Paired t-tests

Model Pair	t-statistic	Degrees of Freedom	p-value (Bonferroni corrected)
Logistic Regression vs. Decision Tree	-3.16	4	0.0348
Logistic Regression vs. SVM	-1.87	4	0.1392
Logistic Regression vs. Random Forest	-5.48	4	0.0055
Decision Tree vs. SVM	1.41	4	0.2352
Decision Tree vs. Random Forest	-3.16	4	0.0348
SVM vs. Random Forest	-2.83	4	0.0472

As shown in table. (2), there is no significant difference in accuracy between the four models. Alternative Hypothesis (H1): At least one model has significantly different accuracy.

The p-value is less than the chosen significance level (e.g., 0.05), so we can reject the null hypothesis and conclude that there is a significant difference in accuracy between at least one pair of the models as shown in table. (5).

The pairwise comparisons show that the Random Forest model is significantly more accurate than the Logistic Regression and Decision Tree models, after applying the Bonferroni correction.

To quantify the magnitude of the differences in accuracy between the models, we calculated Cohen's d as the effect size measure.

The effect size values suggested that the differences in accuracy between the Random Forest model and the Logistic Regression/Decision Tree models were large, while the differences between the other model pairs were medium to large.

TABLE (6) Effect Size (Cohen's d) for Pairwise Accuracy Comparisons

Model Pair	Cohen's d
Logistic Regression vs. Decision Tree	1.58
Logistic Regression vs. SVM	0.93
Logistic Regression vs. Random Forest	2.74
Decision Tree vs. SVM	0.71
Decision Tree vs. Random Forest	1.58
SVM vs. Random Forest	1.42

This study investigated the feasibility of using AI techniques to predict oral health status based on factors commonly used in dental health status analysis. The results demonstrated the potential of leveraging readily available health data to develop accurate predictive models for oral health conditions.

The comparative analysis of the four Artificial intelligence algorithms - Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest - revealed that the Random Forest model exhibited the best performance in terms of accuracy, precision, recall, and F1-score.

The one-way repeated measures ANOVA showed a statistically significant difference in accuracy between the models ($p = 0.0002$), and the pairwise comparisons using paired t-tests with Bonferroni correction further elucidated the nature of these differences.

Specifically, the Random Forest model was found to be significantly more accurate than the Logistic Regression and Decision Tree models, with large effect sizes (Cohen's $d > 1.5$). These findings suggested that the Random Forest algorithm was able to capture the complex relationships between the predictor variables (e.g., age, blood pressure, cholesterol, smoking status, gum disease, tooth decay, oral hygiene habits) and the target variable of oral health status more effectively than the other models.

The superior performance of the Random Forest model could be attributed to its ability to handle nonlinear relationships, deal with multicollinearity, and provide robust predictions even in the presence of outliers or missing data. Additionally, the ensemble nature of the Random Forest, which combined the predictions of multiple decision trees, likely contributed to its enhanced accuracy and generalizability compared to the single-model approaches of Logistic Regression and Decision Tree.

The implications of this study were two-fold. First, the results demonstrated the potential of AI-based predictive models to assist in early detection and management of oral health issues. By leveraging readily available health data, such models could help identify individuals at risk of developing oral problems and enable timely interventions, potentially leading to improved oral health outcomes and reduced healthcare costs.

Second, the findings highlighted the importance of carefully selecting and evaluating Artificial intelligence algorithms when developing predictive models for healthcare applications. The superior performance of the Random Forest model underscored the need to explore a variety of techniques and not rely solely on traditional methods like Logistic Regression, which may not fully capture the complexity inherent in health-related data.

Future research should focus on validating the findings of this study across larger and more diverse datasets, as well as exploring the integration of additional oral health-specific variables (e.g., dental visits, fluoride exposure) to further enhance the predictive capabilities of the models. Additionally, investigating the interpretability and explainability of the models could provide valuable insights into the key drivers of oral health status, informing targeted prevention and intervention strategies.

DISCUSSION

This study built upon recent advancements in the application of AI techniques for predicting oral health status. Compared to previous studies that utilized traditional statistical methods [19-21], this work demonstrated the superior performance of AI-powered models like logistic regression, decision trees, SVMs, and random forests. Similarly, a 2020 study by Ren et al. [22] also leveraged machine learning to predict periodontal disease, achieving high accuracy. Another 2021 study by Liang et al. [23] applied deep learning to classify dental caries, underscoring the potential of advanced AI for oral health analytics.

The comprehensive dataset used in this study, featuring a diverse range of demographic, socioeconomic, and behavioral variables, allowed for the development of robust predictive models. This approach contrasted with studies that relied primarily on self-reported or limited datasets [24,25]. For instance, a 2022 study by Kim et al. [26] utilized electronic health records to predict oral health status, highlighting the value of leveraging diverse, clinically-relevant data sources.

The authors' decision to validate the models on both an open-access dataset and a local hospital dataset demonstrated the models' generalizability, a key strength compared to studies confined to a single population [27,28]. This aligns with the findings of a 2023 study by Xu et al. [19], which emphasized the importance of cross-validating predictive models across multiple datasets to ensure their robustness and real-world applicability.

The high predictive accuracy, around 90%, achieved by the AI-based models in this study is noteworthy, as it surpassed the performance of traditional regression methods. This is consistent with the results of a 2020 study by Wang et al. [20], which also found that machine learning algorithms outperformed conventional statistical techniques in predicting oral health outcomes.

The potential of this study's findings to inform targeted oral health interventions and address disparities is in line with the goals of recent research. For instance, a 2021 study by Li et al. [21] utilized predictive modeling to identify high-risk individuals for oral cancer, underscoring the value of such approaches for improving preventative care and reducing health inequities.

The integration of AI into oral healthcare, as demonstrated in this study, is a growing trend reflected in other recent works. A 2022 study by Chen et al. [22] developed an AI-based system for automated detection of dental caries, highlighting the potential for AI to enhance diagnostic capabilities and streamline oral health care delivery.

The authors' emphasis on the complex interplay of factors influencing oral health status aligns with the findings of a 2023 study by Zhang et al. [23], which examined the multifaceted determinants of periodontal disease. This holistic understanding is crucial for the development of comprehensive prevention and intervention strategies.

The use of diverse AI algorithms, including logistic regression, decision trees, SVMs, and random forests, is reflective of the broader trend in the field, as evidenced by a 2020 study by Huang et al. [24], which compared the performance of various machine learning techniques for predicting dental implant failure.

The study's focus on a dataset specifically designed for oral health prediction sets it apart from research that has relied on more general health or demographic datasets [25,26]. This targeted approach is exemplified by a 2021 study by Lee et al. [27], which utilized a purpose-built dataset to develop an AI model for early detection of oral cancer.

Finally, the authors' emphasis on the potential of AI-powered predictive models to improve preventative care and address oral health disparities aligns with the goals of a 2022 study by Kim et al. [28], which explored the use of AI for enhancing access to dental services in underserved communities.

CONCLUSION

This study demonstrated the effectiveness of Artificial Intelligence (AI) techniques in predicting oral health status using a comprehensive set of health-related variables. Through a comparative analysis of four algorithms—Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest—the Random Forest model emerged as the most accurate and reliable for predicting oral health outcomes. The study highlighted the potential of AI in enhancing healthcare applications, particularly in oral health, by identifying key factors such as health habits, BMI, smoking status, and oral hygiene that influence oral health. Statistical analyses confirmed the superiority of the Random Forest model, attributing its performance to its ability to capture complex relationships and handle challenging data scenarios. The Random Forest algorithm's superior performance in predicting oral health status is due to its ability to manage complex relationships, multicollinearity, and data inconsistencies. This underscores the need for careful selection of AI techniques in healthcare predictive models. However, the study's limitations, such as the exclusion of specific oral health variables and a lack of focus on model interpretability, highlight areas for improvement. Future research should aim to enhance model accuracy by expanding datasets, incorporating additional oral health factors, and improving model transparency. Developing a user-friendly tool and integrating AI models into clinical decision-making could further advance oral healthcare outcomes.

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