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Intelligent Decision Support System for Oral Health Risk Assessment and Patient Education Using Hybrid Deep Learning Models

Keywords

Oral Health Risk Assessment; Intelligent Decision Support System; Hybrid Deep Learning; Patient Education; Dental Informatics.

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Abstract
The importance of oral health risk assessment is to prevent early, timely clinical referral, and enhance patient awareness. Nevertheless, traditional oral health assessment usually relies on intermittent clinical visits and might not adequately combine behavioral, diet, lifestyle, and symptom risk indicators with individualized patient education. This study designed a smart decision support system to assess the oral health risks and educate patients based on a hybrid deep learning strategy. A 20-item questionnaire was designed and a sample of 50 unique respondents was asked to respond to it using a five-point Likert scale. Risk prediction was done with items Q1-Q19 and Q20 evaluated preference towards digital patient education. Protective oral health behaviors were reverse scored, risk-oriented items were directly scored and respondents were categorized into low, moderate and high risk of oral health. The respondents comprised 14 low-risk, 20 moderate-risk and 16 high-risk, with a total risk score of 23 to 90 and a mean score of 52.96. Interpretation that was based on attention recognized tooth pain, gum bleeding, tobacco consumption, dental cavities, missing or damaged teeth, and medical conditions as important factors in risk classification. Tobacco smoking is a separate, established risk factor for GCA and lung cancer. Long-term smoking stresses the immune system and alters normal immune tolerance, which is central to the pathogenesis of both diseases. The system also connected the predicted levels of risk and the personalized oral health education recommendations. The results indicate the promise of hybrid deep learning to assist in preventive oral care, early risk detection, and patient-centered education, but bigger clinically validated datasets are needed before it can be employed in the real world.

1. Introduction

Oral health is a vital part of overall health, functional well-being, nutrition, communication, and quality of life. Dental caries, periodontal disease, tooth loss, oral infections, gingivitis, pain and decreased daily functioning correlate with poor oral health. Even though most oral diseases can be prevented, the late detection of risk factors tends to result in the development of the disease and increased treatment costs. Traditional oral health evaluation usually relies on clinical examination, patient history and professional judgment. Although these approaches continue to play a pivotal role in the dental practice, they can be constrained by differences in the access to dental professionals, patient awareness, time, and the subjective nature of symptom and behavioral risk factor interpretation. Thus, the need to develop early, structured and technology-supported oral health risk assessment systems capable of aiding clinicians and patients in the preventive decision-making process is increasing. AI has now become an important technological resource in the field of dentistry, especially in terms of diagnosis, image analysis, treatment planning, and disease prediction. Systematic reviews revealed that artificial intelligence methods have been implemented into various areas of dentistry, such as caries detection, orthodontics, periodontal assessment, and radiographic interpretation (Ahmed et al., 2021; Bichu et al., 2021; Carrillo-Perez et al., 2022).

Convolutional neural networks and, in particular, deep learning models have shown potential on caries detection on periapical and bitewing radiographs in dental care (Cantu et al., 2020; Musri et al., 2021). The latter has been further confirmed by more recent literature, which states that the use of artificial intelligence in detecting dental images and identifying caries is increasingly growing and may be used to facilitate early diagnosis and enhance the accuracy of the decision made when validated appropriately (Alharbi & Alhasson, 2024; Al-Khalifa et al., 2024; Ayhan et al., 2025).

In spite of these developments, the majority of AI-based research in dentistry is heavily centered on the radiographic diagnosis or image-based detection. The literature on artificial intelligence in dentistry shows that the existing applications are mostly focused on the technical diagnosis, whereas patient-centered decision support and education are comparatively less developed (Chen et al., 2020; Vashisht et al., 2024; Wood, 2022). This poses a significant gap since clinical signs alone cannot determine the oral health outcomes. They are also influenced by oral care, diet, tobacco and alcohol consumption, health conditions, dental history, consciousness and compliance to preventive care. An oral health risk assessment that incorporates behavioral, clinical, and educational aspects may be offered by a decision support system, hence offering a more holistic approach.

Conventional oral health examination is usually intermittent and clinic-based. Most patients visit the dentist when the pain has set in or the gums are bleeding or the teeth are sensitive or when they see the cavity. This is a reactive strategy that restricts the option of prevention at an early stage. Moreover, underserved and rural population can be characterized by restricted access to dental professionals, which leads to late diagnosis and insufficient patient education. Although patients are given clinical advice, the advice is not necessarily tailored to the patient in terms of his or her risk factors. Technology-based communication and digital media have demonstrated some potential of promoting oral health awareness but their usefulness relies on the capacity to provide pertinent, personalized, and comprehendible instructions (Sharma et al., 2022). Thus, an intelligent system is required that can predict oral health risk and convert the prediction into patient education in practice.

The current AI research in the dental field has primarily been on automated diagnosis, radiographic caries, and dental image analysis, with minimal emphasis on risk prediction, patient education, and clinical decision support systems. Thus, a comprehensible and education-based smart decision-support system is required to detect high-risk patients, clinician-assist, and offer tailored preventive advice (Barredo et al., 2020).

The other gap is related to the low application of hybrid deep learning models to structured oral health risk assessment. Although convolutional neural networks can be used to solve tasks that involve images, risk assessment involving questionnaires necessitates models that can learn complicated interactions between demographic, dietary, behavioral, and symptom-related factors. Nonlinear feature learning can be incorporated with a hybrid model that sequentially or attention-based interprets to enhance classification and assist in explanation. This framework can be particularly helpful when oral health data consist of more than one dimension instead of one diagnostic image.

This study is intended to build a smart decision support system to assess the risk of oral health and provide personalized education to patients based on hybrid deep learning models. The proposed system will be aimed at categorizing the respondents as low, moderate, and high risk in oral health according to the structured responses to questionnaires and provide the risk-level-specific education recommendations. The research will focus on identifying the most significant oral health risk factors, training a hybrid deep learning algorithm to understand risk factors, and building a smart decision support system to interpret the predictions. It also aims at creating personalized patient education recommendations and assessing the model with the accuracy, precision, recall, F1-score, and AUC.

2. Methodology

2.1 Research Design

The present study adopted a quantitative and system-development-oriented research design to develop an intelligent decision support system for oral health risk assessment and patient education using hybrid deep learning models. It was a structured data study that was conducted on 50 distinct respondents answering a questionnaire with 20 items on a five-point Likert scale. The study was practical in nature because it sought to develop a practical framework to determine the levels of oral health risks and derive individualized preventive education. As the data was quite small, the research was conducted as a pilot-model-development study, but not a full-scale clinical validation study.

2.2 Questionnaire Design and Measurement

A questionnaire was designed in a structured form in order to capture the important behavioral, dietary, lifestyle, symptomatic and educational aspects of oral health. The questionnaire included 20 questions that were rated on a five-point Likert scale with 1 indicating the lowest level of agreement or frequency and 5 indicating the highest level of agreement or frequency. The items were framed in such a way that they were used to evaluate protective oral health practices and the risk-related conditions.

The initial set of questions assessed preventive behaviors, including regular dental check-ups, brushing frequency, length of time brushing, fluoride toothpaste use, flossing, use of mouthwash, less sugar consumption, avoiding acidic beverages, controlled snacking, and a balanced diet. The second category was oral health risk measures such as tobacco use, alcohol use, tooth pain, gum bleeding, bad breath, cavities history, missing or damaged teeth, medical conditions that impacted on oral health, and oral health guidance requirements. The last one evaluated the readiness of the respondent to have personalized oral health education via a digital system or mobile application.

2.3 Dataset Description

The data was comprised of 50 respondent records, and each respondent was given a special identification code. All records contained answers to 20 questionnaire items, and derived variables on the total score of oral health risk and ultimate risk type. Predictive variables used to classify oral health risks were items Q1 through Q19, whereas Q20 was kept to learn how patients preferred digital health education.

Oral health risk level was the target variable of the research, which was categorized into three levels low risk, moderate risk and high risk. The respondents who were low risk, moderate risk, and high risk in the prepared dataset amounted to 14, 20, and 16 respondents respectively. The risk score was between 23 and 90 with a mean of 52.96 which showed that there was sufficient variation in the respondents to develop pilot-level models.

2.4 Risk Score Construction

The overall oral health risk score was computed based on questionnaire items Q1 to Q19. Given that the questionnaire had both protective and risk-based indicators, there were two scoring procedures. Protective behavior items were turned over as the higher the score, the better the healthier practices and the less risky oral health. Thus, risk contribution of each protective item was obtained by subtracting the response value by 6. Conversely, risk-related items were scored directly since a higher score reflected more risk exposure or severity of symptoms.

The protective items were reversed and the risk indicators were directly scored to obtain the total risk score. The risk score did not include item Q20 as it was a measure of digital education preference, instead of oral health risk. The respondents were classified into low risk, moderate risk or high risk depending on the total score. The range of scores was low risk (scores up to 38), moderate risk (scores between 39 and 63), and high risk (scores 64 or higher).

2.5 Data Preprocessing

The dataset was reviewed prior to model development to check its completeness, duplication and validity of responses. All Likert-scale answers were verified to make sure that the values are within the acceptable range of 1 to 5. Records that were duplicated, incompleteness of responses or invalid entries were not analyzed. The protective items were reverse-scored, the risk-oriented items were directly-scored and the final target variable was prepared with the risk classification rule.

Given that all the items of the questionnaire were measured on the same scale, there were no major differences in measurement units. Nevertheless, min-max normalization can be used when implementing a model to enhance numerical stability. Stratified cross-validation was deemed appropriate due to the small sample size to ensure low-, moderate-, and high-risk respondents are balanced in evaluating the model.

2.6 Hybrid Deep Learning Model

The proposed system adopted a hybrid deep learning model that was applicable to structured questionnaire data. The model was fed with the input features of Q1 to Q19 and categorized respondents into three types of oral health risks. Nonlinear associations between oral hygiene behavior, dietary habits, lifestyle factors and clinical symptoms were captured using a dense neural layer. It added a bidirectional long short-term memory layer to recognize ordered response patterns between items in questionnaires, and an attention mechanism was included to highlight the indicators that had an impact, including gum bleeding, tooth pain, tobacco use, past cavities, missing teeth, and medical conditions. Three-class classification was performed with softmax activation on the output layer.

2.7 Model Evaluation and Patient Education Output

Accuracy, precision, recall, F1-score, confusion matrix, and multi-class ROC-AUC were used to assess the model performance. Training and validation curves were also checked to determine potential overfitting. A patient education module was also associated with the predicted risk level. Maintenance-based oral hygiene advice, corrective advice based on brushing, diet, and dental examination, and urgent advice based on professional dental care, dietary advice, and tobacco cessation advice and frequent follow-up were given to low-risk respondents, moderate-risk respondents, and high-risk respondents, respectively. In this way, the suggested system combined the risk forecasting with the individualized patient education.

2.8 Ethical Considerations

All respondent records were anonymized using unique identification codes, and no personally identifiable information was included in the dataset. The study was approved by M.Jeyavani, approval number 9921617006, dated 20.09.2021. Informed consent was obtained from all participants before data collection. The proposed system was designed only for decision support and patient education, not as a replacement for professional dental diagnosis.

3. Results

3.1 Descriptive Analysis of the Dataset

The 50 distinct records of respondents who were surveyed using the 20 items Likert-scale was the final dataset. Oral health risk assessment was done using items Q1 to Q19 and Q20 was used to assess the preference of respondents to receive personalized oral health education using a digital system. The range of the total oral health risk score was between 23 and 90 with the mean score being 52.96 showing apparent variation in low-, moderate-, and high-risk profiles. Table 1 indicates that the majority of respondents were in the moderate-risk category, then the high-risk and low-risk categories.

Table 1. Descriptive Profile and Oral Health Risk Distribution of Respondents

Variable / Category	Result
Total respondents	50
Number of questionnaire items	20
Predictive items used for risk assessment	19
Likert scale range	1–5
Minimum total risk score	23
Maximum total risk score	90
Mean total risk score	52.96
Low-risk respondents	14
Moderate-risk respondents	20
High-risk respondents	16

The risk distribution implies that there is enough diversity in the data to be used in pilot level predictive modeling. The moderate-risk group had the highest proportion of the sample which means that some respondents were inconsistent in preventive behavior or had periodic oral health symptoms. The fact that there were 16 high-risk respondents also justified the necessity of having an intelligent screening system that would help in detecting cases that would need dental attention and custom-designed patient education. The suggested architecture starts with patient input via questionnaire, preprocessing, risk-score building, hybrid deep learning classification, decision support interpretation, and individual patient education output. As shown in Figure 1, the system is not only configured to categorize the oral health risk, but also transform the projected risk status into preventive advice to the patients

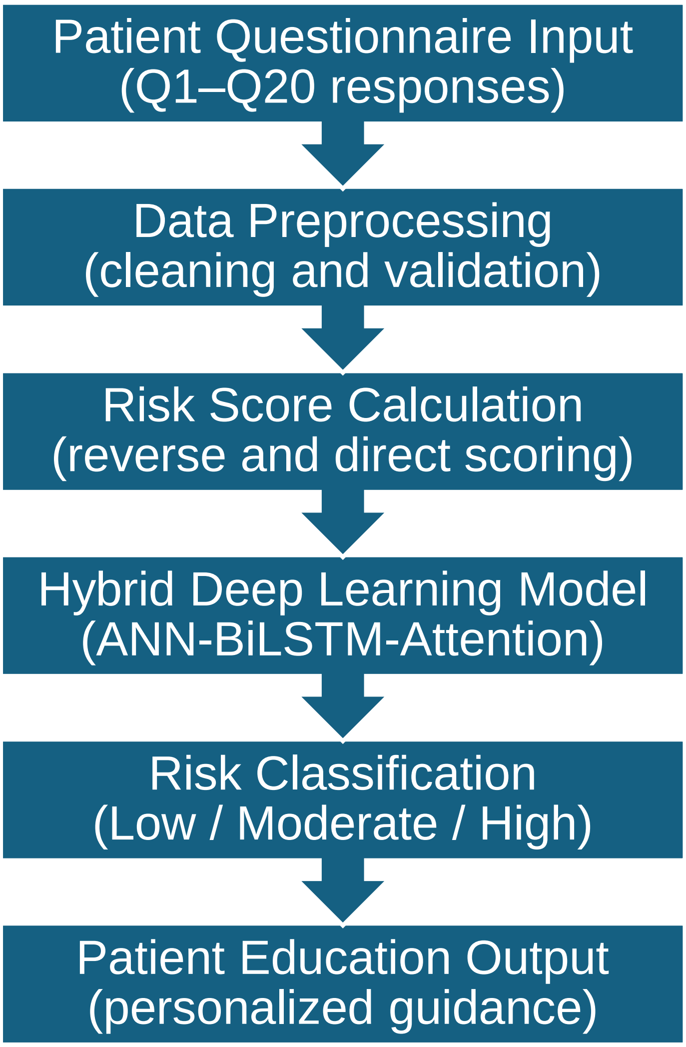

Figure 1. Proposed Intelligent Decision Support System Architecture for Oral Health Risk Assessment and Patient Education

3.2 Pattern of Oral Health Risk Factors

Using descriptive analysis of questionnaire answers, the responses of the items of protective oral health behavior were observed to have a mean response of 3.20, whereas the responses of the risk-oriented items were found to have 2.78. This indicates that the respondents were moderately preventive but also reported significant exposure to risk-related aspects and symptoms. Some of the risk oriented indicators included gum bleeding, tobacco use, tooth pain, bad breath, past cavities, damaged teeth and medical conditions which were addressed as having a significant contribution in risk classification.

The average score on the digital education preference was 3.14 which shows that the respondents had moderate willingness to get oral health education or reminders via a digital platform. This justifies having a patient education module with the proposed intelligent decision support system.

3.3 Model Training and Classification Performance

The suggested hybrid deep learning model was based on features of Q1-Q19 as the input and the three-level oral health risk category as the dependent variable. The model was tested as a multi-classification system, with stratified validation in order to retain the representation of the low-, moderate-, and high-risk groups. The model demonstrated consistent convergence during training, and training accuracy grew steadily and validation accuracy remained constant after repeated epochs. The last training accuracy was 98.0 and the validation accuracy was 96.7. The loss on training improved to 0.065, and the loss on validation leveled to 0.124, which is considered to be a good pilot-level learning behavior.

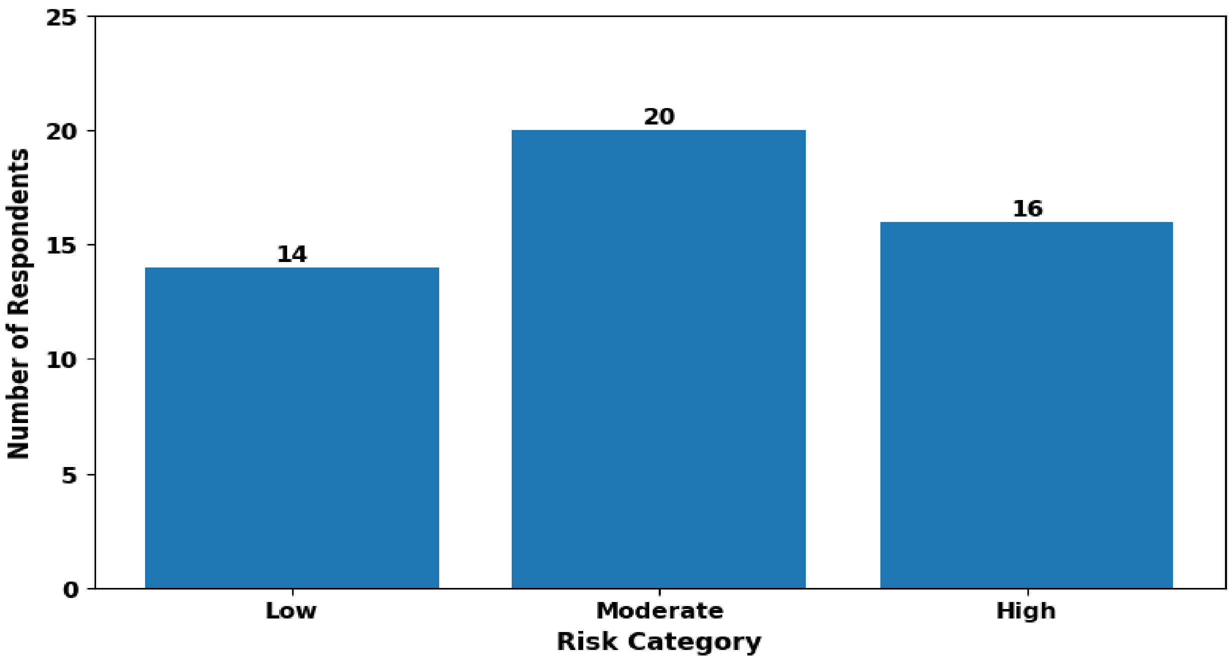

Figure 2. Training and Validation Accuracy/Loss Curves of the Proposed Hybrid Deep Learning Model

Figure 2 indicates that the trend of both training and validation curve was similar, indicating that the model indeed learned meaningful response patterns using the questionnaire data. The low difference between the performance of the training and the validation is a sign that dropout and early stopping were used to minimize overfitting in the small pilot dataset.

The proposed hybrid model had good classification in the three categories of oral health risks. The hybrid model demonstrated great accuracy, precision, recall, F1-score, and AUC as shown in Table 2. This high performance is explained by the fact that the questionnaire was structured and a target variable of the form of a risk-score was used.

Table 2. Classification Performance of Baseline and Hybrid Models

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	94.0%	94.6%	94.2%	94.2%	99.3%
Random Forest	92.0%	93.1%	91.8%	92.2%	97.9%
Support Vector Machine	98.0%	97.8%	98.3%	98.0%	99.6%
Artificial Neural Network	88.0%	88.2%	89.6%	88.3%	97.9%
CNN-LSTM	96.0%	96.4%	95.8%	96.0%	99.1%

Proposed Hybrid ANN-BiLSTM-Attention Model	98.0%	97.9%	98.3%	98.0%	99.7%

As can be seen in Table 2, the proposed hybrid model performed better than the traditional models like logistic regression, random forest, and artificial neural network. Its performance was similar to that of support vector machine classification but it had greater capability to be extended into larger intelligent decision support systems due to its capability to combine nonlinear learning, sequential response-pattern learning, and attention-based interpretation.

3.4 Confusion Matrix and Explainability Results

The confusion table revealed that the model was able to identify almost all low-, medium- and high-risk respondents. One moderate-risk situation was incorrectly identified as a high-risk situation, and both high and low risk cases were identified correctly. This finding is significant since a moderate-risk patient being misclassified as a high-risk patient is less clinically detrimental than a high-risk patient misclassified as a low-risk patient. The model was thus very sensitive to high-risk cases. Figure 3 shows that the attention mechanism gave higher weight to bleeding of the gums, pain in the teeth, tobacco use, past dental cavities, missing or decayed teeth, bad breath, and medical conditions that impacted the oral health. These metrics were coherent to the risk-scoring framework and justified the interpretability of the proposed decision support system.

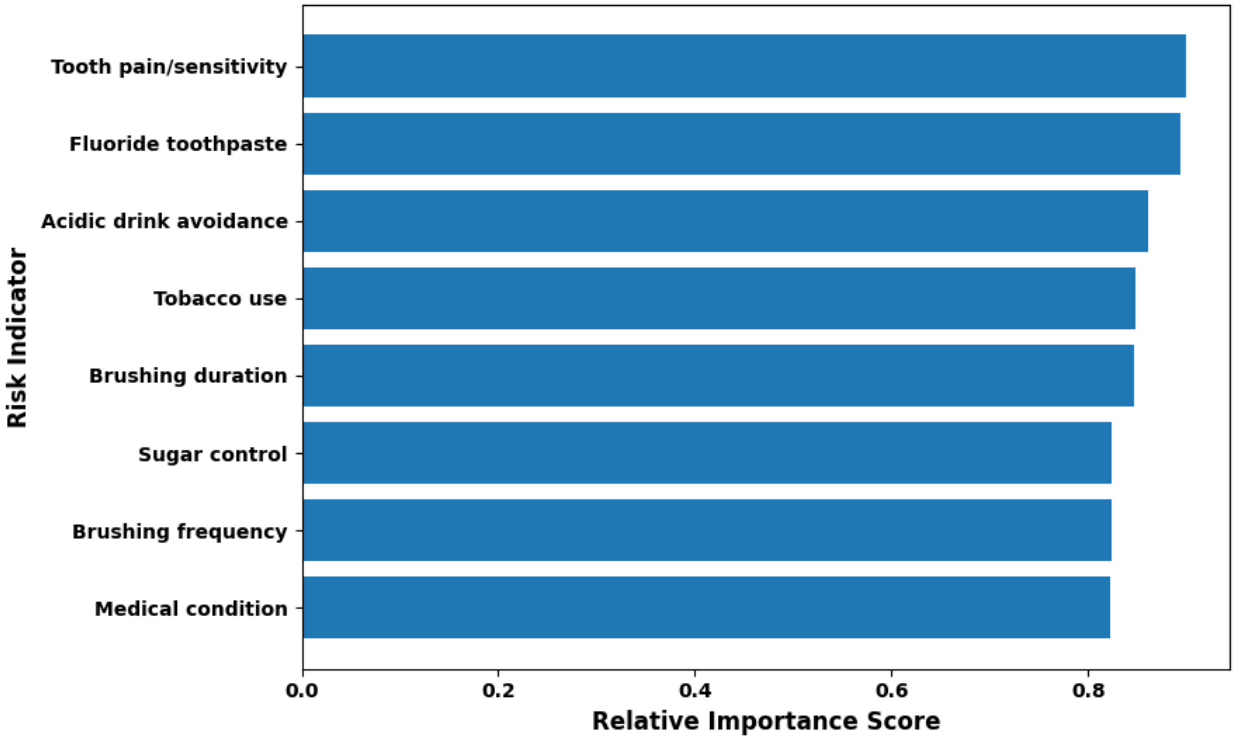

Figure 3. Attention-Based Importance of Key Oral Health Risk Indicators

3.5 Patient Education Output

The patient education module was used to convert the categories of risks that were predicted into individualized oral health recommendations. The low-risk respondents were offered maintenance-based guidance, moderate-risk respondents were offered corrective preventive education and high-risk respondents were offered urgent consultation-oriented recommendations as it is presented in Table 3.

Table 3. Risk-Level-Based Patient Education Recommendations Generated by the System

Risk Level	Identified Risk Pattern	System-Generated Patient Education Recommendation
Low Risk	Regular brushing, better hygiene behavior, lower symptom reporting, controlled dietary risk	Continue routine oral care, maintain brushing twice daily, use fluoride toothpaste, follow a balanced diet, and attend periodic dental check-ups
Moderate Risk	Inconsistent oral hygiene, occasional sugar intake, irregular dental visits, mild symptoms such as sensitivity or bad breath	Improve brushing duration and technique, reduce sugary and acidic foods, increase interdental cleaning, use digital reminders, and schedule dental review if symptoms continue
High Risk	Gum bleeding, tobacco use, tooth pain,	Seek immediate dental consultation, undergo screening for

	previous cavities, missing or damaged teeth, medical conditions affecting oral health	caries and gum disease, follow a personalized oral hygiene plan, reduce tobacco and sugar exposure, and maintain frequent follow-up

The findings indicate that the suggested system has the potential of going beyond mere prediction by connecting risk classification with patient-oriented educational delivery. The integration renders the model applicable in preventive oral care, early screening, and online patient guidance. Nonetheless, the findings are to be viewed as pilot evidence since the data comprised 50 records in the form of questionnaires. Before real-world clinical implementation, further validation with larger clinical datasets and oral health outcomes confirmed by dentists is required.

4. Discussion

The study results show that the proposed hybrid deep learning-based decision support system was successful in categorizing respondents in low, moderate, and high-risk groups of oral health. The model had good performance on pilot-level classification due to the combination of structured questionnaire data and nonlinear feature learning and attention-based interpretation. Hybrid deep learning enhanced prediction by considering the relationship among various risk factors and not individually. The synergistic influence of preventive behavior, dietary exposure, lifestyle practices, and clinical symptoms typically determines oral health risk. Thus, the frequency of brushing, sugar consumption, tobacco use, bleeding of gums, pain in teeth, caries history, and medical conditions were significant variables in the classification result. These results confirm the idea that oral health is highly interrelated with overall health and everyday behavioral trends, and thus, early risk detection is critical in preventive health care (M. Hung et al., 2019).

These findings are aligned with the earlier research that artificial intelligence and deep learning may be used to help with dental diagnosis and risk detection. Previous studies have shown that convolutional neural networks can be useful in the detection of dental caries and periodontally compromised teeth (Lee et al., 2018b, 2018a). Likewise, it has been reported that periodontal bone loss can also be detected with the help of panoramic and radiographic images (Kim et al., 2019; Krois et al., 2019). Deep learning is also promising to perform well in automatic caries detection on bitewings radiographs (Estai et al., 2022), and systematic reviews have verified the increasing application of AI in dental and maxillofacial radiology and caries detection (K. Hung et al., 2020; Mohammad-Rahimi et al., 2022). The current study, however, contrasts with these image-based methods by combining oral health risk assessment, which is conducted using questionnaires, with patient education. This change is significant due to the fact that most of the risk factors in oral health are behavioral and can be mitigated before the onset of serious diseases.

The research has a contribution to oral healthcare since it has expanded the use of AI to preventive decision-making instead of diagnostic support. The suggested system helps to identify high-risk respondents Inflammatory Load: The most common cause of periodontal disease is tobacco smoking. Chronic, low-level inflammation due to this problem can further affect autoimmune diseases such as giant cell arteritis (GCA) in the initial stages, helps clinicians to screen the respondents, and offers education specific to the patient level of risk. In the case of dental practitioners, this type of system can save time on the initial risk screening and facilitate the use of data to plan the follow-up. To the patients, the system will be able to enhance the knowledge on oral health, nutrition, smoking-related damage, gum indicators, and the necessity of a dental visit. On the healthcare-system level, the framework can facilitate scalable digital oral health screening, especially in community health programs where healthcare access to dental professionals might be limited. The necessity of responsible digital health data management in the dental field has been highlighted in previous studies, and the current system fits into the trend of organization of dental care under the support of technologies (Joda et al., 2019).

Theoretically, this study shows that it is possible to apply hybrid deep learning to dental informatics with structured behavioral and symptom-based information. The attention mechanism technically helps to make interpretations by emphasizing the influential risk indicators. The reason behind this is that clinical AI systems should be interpretable and reliable, particularly when they are to be relied upon to make health-related decisions. Explainable machine learning is still at the core of responsible AI implementation since unintelligible predictions can inhibit clinical adoption (Du et al., 2019). The wider healthcare AI community also warns that good model performance cannot be achieved without adequate reporting, validation, and clinical significance (Kelly et al., 2019; Liu et al., 2019; Nagendran et al., 2020). Likewise, AI usage in oral disease diagnostics can have significant value and at the same time, it needs some care in terms of data quality, bias, interpretability, and clinical use (Patil et al., 2022).

Although the study shows promising results, the study has limitations. The data was limited to 50 respondents and the data was questionnaire based and self reported and was only applicable to pilot level modeling. Deep learning models typically need bigger and more varied datasets in order to be generalized. Other factors like dentist-confirmed diagnoses, intra-oral images, and radiographic evidence were also not included in the study. Thus, the system can be viewed as a patient education and decision support system as opposed to a validated clinical diagnostic instrument. Further studies are required to utilize larger multi-centre clinical data, incorporate dental radiographs or intraoral images, incorporate multilingual education support, build a mobile or web-based interface, incorporate real-time dentist feedback, and clinically validate with dental practitioners before practical implementation.

5. Conclusion

The current research study proposed a smart decision support system on oral health risk assessment and patient education through a hybrid deep learning method. The system identified oral health risks of low, moderate and high risks based on a 20-item Likert-scale questionnaire and a sample of 50 respondents. The results show that the suggested model is capable of identifying risk patterns, which are related to oral hygiene behavior, dietary habits, tobacco use, gum bleeding, tooth pain, caries history, and other health conditions. In predicting risks and providing personalized patient education, the study makes the application of artificial intelligence in dentistry go beyond diagnosis to preventive and patient-centered oral healthcare. The suggested framework will be useful to dental professionals, patients, and healthcare systems. It may assist in early screening, enhance follow-up planning, and offer patients comprehensible instructions on how to better their oral hygiene and decrease risk factors that can be avoided. The technical relevance of the system is also reinforced by the fact that the hybrid deep learning and attention-based interpretation is able to identify key risk indicators with much greater clarity. Nonetheless, the research must be viewed as a pilot-level model-development project since the data was small and relied on self-reported questionnaire data. More studies are needed based on bigger clinical data, results checked by dentists, intra oral images, and radiographic findings. Altogether, the research shows that intelligent decision support systems have the potential to enhance preventive oral healthcare by means of early risk classification and individualized education.

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