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EXPERT SYSTEM APPLICATION DESIGN FOR ENHANCED DENTAL DISEASE DIAGNOSIS

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Abstract

Dentistry is an ever-evolving field, and nowadays, there's a strong emphasis on harnessing technology to improve the diagnosis and treatment of dental diseases. We all know how common issues like cavities, gum disease, and oral infections can lead to serious oral health problems if not dealt with properly. In the past, dentists relied solely on their skills and experience to diagnose these conditions. They would manually examine patients, study the data, and take into consideration the patient's medical history to arrive at a diagnosis. While this approach has served dentistry well for many years, it does come with its limitations. One of the drawbacks is the possibility of human errors and biases affecting the accuracy of diagnoses. Additionally, the time-consuming process of manually analyzing large datasets slows down the diagnosis. What's more, the traditional approach lacks the ability to integrate real-time updates from the latest dental research and advancements in dental care. As a result, there's a growing demand for a smarter system that can aid dentists in making quicker and more precise diagnoses. To address these challenges and improve the accuracy and efficiency of dental disease diagnosis, experts have been exploring the potential of expert systems, a type of artificial intelligence (AI) that mimics human decision-making abilities. These systems have the capacity to revolutionize dental diagnosis by providing timely and accurate assessments, leading to more effective treatment plans and better patient outcomes.

1. Introduction

Designing an expert system for enhanced dental disease diagnosis involves the creation of a specialized software application that leverages artificial intelligence and domain-specific knowledge to assist dental professionals in accurately diagnosing and treating oral health issues. This system aims to streamline the diagnostic process, reduce human errors, and improve the overall quality of dental care. The core of this expert system is its knowledge base, which contains a vast repository of dental information, including symptoms, causes, risk factors, and treatment options for various dental diseases and conditions. This knowledge is structured in a way that mirrors the decision-making process of a skilled dentist. To develop the knowledge base, a team of experts in dentistry, along with AI specialists, collaborate to ensure that the system's information is up-to-date and comprehensive. The system also incorporates a rule-based inference engine that uses logical rules and algorithms to analyze patient data. Dentists or dental hygienists input patient information such as medical history, symptoms, and diagnostic test results into the system. The expert system then applies its knowledge to suggest potential diagnoses and treatment recommendations. It can also provide a list of differential diagnoses, helping practitioners consider various possibilities. User interaction is a crucial aspect of the application design. The system should have a user-friendly interface that allows dental professionals to input patient data easily and receive clear and concise diagnostic recommendations. It can also provide educational materials and explanations to help clinicians understand the reasoning behind the system's suggestions. Furthermore, to enhance its capabilities, the expert system can be integrated with imaging technology like X-rays and intraoral cameras. By analyzing these visual data, it can assist in identifying dental conditions that are not immediately apparent through patient-reported symptoms alone.

2. Literature Survey

Over the past decade, artificial intelligence (AI) has made remarkable contributions to various subdisciplines falling under the category of dentistry, specifically periodontology. Different studies have explored dental disease detection, localization, classification, and segmentation within the dental domain (e.g., [1]). However, few studies have explored dental disease localization as discussed in the literature. From the existing literature, several challenges are found regarding dental carious region localization. A comprehensive overview of existing studies is presented in Table 1. Further exploration is required to propose detection and localization approaches for dental caries diagnosis in real time. To classify enamel, dentin, and pulp caries, Oprea et al., proposed rule-based classification. The authors were able to categorize regions as dentin caries sized over 2 mm [9]. Another rule-based approach based on the gradient histogram and threshold was proposed by ALbahbah and fellow authors on panoramic radiographs to extract and segment decayed and normal teeth [10]. Lin et al., investigated the level segmentation method based using SVM (support vector machine), KNN (K nearest neighbor), and a Bayesian classifier for localizing alveolar bone loss [11]. Results show that the model can localize alveolar bone loss with higher classification accuracy. A cluster-based segmentation technique was proposed by Datta and Chaki to detect dental cavities in [12]. The proposed model utilized a Wiener filter to extract caries lesions followed by region segmentation to monitor the lesion size and growth. To detect and classify proximal carious and non-carious lesions on panoramic radiographs, Na'am et al., explored multiple morphological gradient-based image processing methods on images with manually cropped regions [13].

Different deep learning approaches have been employed by researchers to pave way for more efficient and effective methods to diagnose dental caries. To classify carious and non-carious teeth on a small, labeled dataset, a pre-trained CNN was utilized by Prajapati et al. [14]. The model was able to classify dental caries, periodontitis, and periapical infection. Lee et al. utilized a deep CNN to diagnose and classify caries using 3000 periapical radiographs [15]. The model achieved an AUC of 0.91 for premolar, 0.89 for molar, and 0.84 for both premolar and molar models. For the identification of dental caries, Cantu et al., investigated U-Net on bitewing radiographs [16]. It was found that segmentation-based models possess the potential to aid dental clinicians in detecting and locating dental caries more efficiently. For the identification of endo-perio lesions on periapical radiographs, Sajjad et al., investigated AlexNet, for which the model achieved an accuracy of 98% [17]. For early identification of dental caries, Kumari et al., preprocessed bitewing radiographic images using contrast limited adaptive histogram equalization (CLAHE) and noise filtering followed by a meta-heuristic based ResneXt RNN (recurrent neural network) [18].

Radiological examinations help dental clinicians in the identification of teeth abnormalities, cysts, infections, and infections. However, manual examinations are time-consuming and rely solely on a specialist's opinion which may bring differences in the diagnosis. Different methods have been employed by researchers in recent years mainly relying on boundary-based, region-based [19], cluster-based, and threshold-based methods [11]. As the first step, Jader et al., employed an RCNN for the segmentation of caries and the detection of missing teeth on buccal images. The results indicated that deep learning-based instance segmentation has the potential to automate the process of caries detection and medical report generation [2]. The faster region-based convolutional neural network (Faster-RCNN), which extends the Fast-RCNN is utilized to localize teeth lesions [5]. The model achieves both a recall and precision of above 90%, however, the model suffers in numbering the teeth in complicated cases. A Faster-RCNN built on the region proposal network (RPN) and object detection network (ODN)

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detected different types of teeth achieving a mean average precision (mAP) of 91.40% and an accuracy of 91.03% [6]. However, the model was applied to a small dataset and performance can not be generalized. Another variant of Faster-RCNN pre-trained on ResNet-50 was employed in [7] for the detection of carious teeth, achieving a precision of 73.49% and an F1 score of 0.68. The model, however, does not identify the type of caries and only localizes the caries region.

An M-RCNN, which extends the Faster-RCNN with pre-trained ResNet-101 was found to be helpful in the identification of missing or broken teeth, achieving an accuracy of 98% [2]. However, segmentation performance metrics were not reported in the study. For pixel-wise segmentation of visible light images for identification of oral cavities [3], M-RCNN achieves an accuracy of 74.4%. However, the dataset is sparse and other relevant performance metrics have not been reported for comparison. In another attempt, an M-RCNN with a fully convolutional network (FCN) and a ResNet-101 backbone [4] was investigated to localize occlusal surface caries on a limited dataset, but the computational complexity was not reported. In a recent attempt, a hybrid M-RCNN [8] was employed to identify dental caries on mixed images achieving an average precision of 81.02% and an accuracy of 95.75%, however, the model does not identify caries type for both colored and X-ray images. Additionally, an M-RCNN with ResNet as its backbone requires a substantial number of calculations to learn and analyze, and the training process for M-RCNN requires high-performance computational resources such as GPU and memory [20].

3. Proposed System Design

Activity diagrams are graphical representations of Workflows of stepwise activities and actions with support for choice, iteration, and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

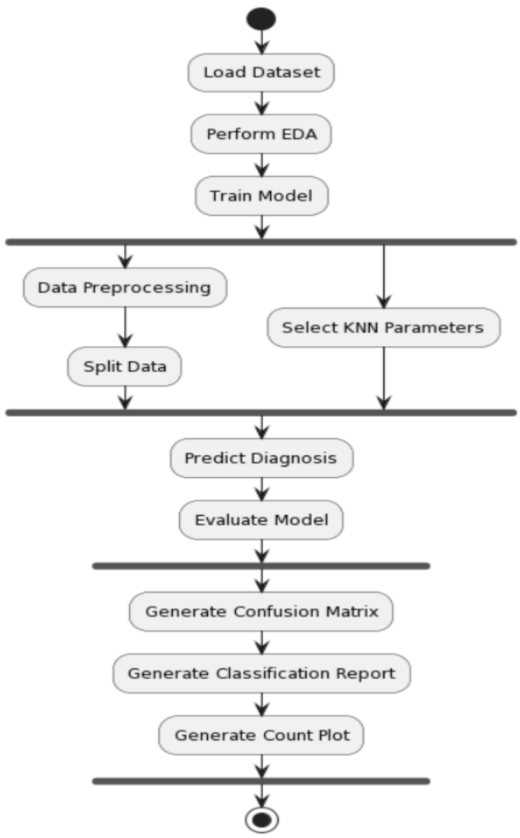

Figure 1. Proposed system design.

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3.1 SVM

SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

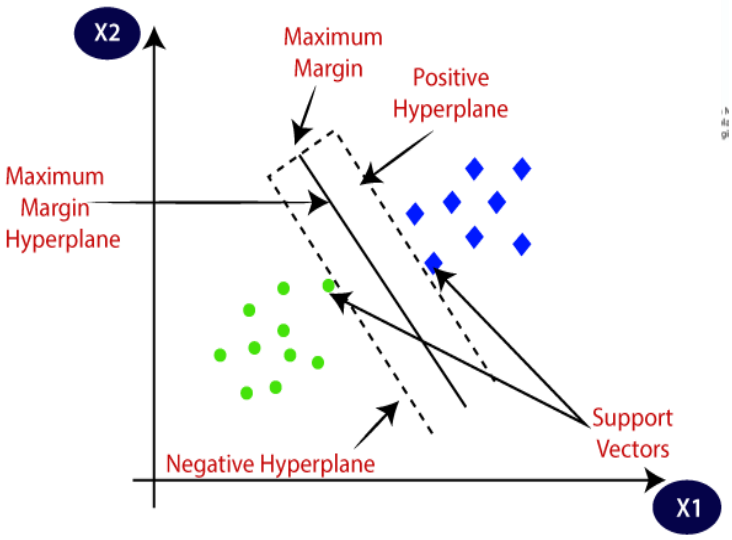

Figure 2: Analysis of SVM.

4. Results and description

The figure below displays a portion of the dataset used for dental diagnosis. It might show a few rows and columns to give an overview of the data, providing a glimpse of how the information is structured.

	GP01	GP02	GP03	GP04	GP05	GP06	GP07	GP08	GP09	GP10	...	GP20	GP21	GP22	GP23	GP24	GP25	GP26	GP27	GP28	Diagnosis
0	0.5	0.75	0.5	0.00	0.0	0.0	0.0	0.75	0.50	0.00	...	0.0	0.00	0.00	0.00	0.0	0.0	0.00	0.0	0.00	Gingivitis
1	0.0	0.00	0.0	0.75	0.0	1.0	0.0	0.50	0.75	0.00	...	0.0	0.00	0.00	0.00	0.0	0.0	0.00	0.0	0.00	Gingivitis
2	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.50	0.75	...	0.0	0.75	0.00	1.00	0.0	0.0	0.00	0.0	0.00	Karies Gigi
3	0.0	0.75	0.0	0.00	0.5	0.0	0.0	0.00	0.00	0.00	...	0.0	0.00	0.00	0.00	0.0	0.0	0.00	1.0	0.00	Periodontitis
4	0.0	0.00	0.0	0.00	0.0	0.0	0.0	1.00	0.25	0.00	...	0.0	0.00	0.00	0.75	0.0	0.0	0.00	0.0	0.00	Karies Gigi
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
95	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.00	0.00	...	0.0	0.00	0.25	0.00	0.0	0.0	0.00	0.0	0.00	Pulpitis
96	0.5	1.00	0.0	0.75	0.0	1.0	0.0	0.00	0.00	0.00	...	0.0	0.00	0.00	0.00	0.0	0.0	0.00	1.0	0.00	Periodontitis
97	0.0	0.00	0.0	0.75	1.0	1.0	0.0	0.00	0.00	0.00	...	0.0	0.00	0.00	0.00	0.5	0.0	0.25	0.0	0.00	Abses gigi
98	0.0	0.00	0.0	0.00	0.0	0.0	0.0	0.00	0.75	0.75	...	0.0	0.00	0.00	0.00	0.0	0.0	0.00	0.0	0.00	Karies Gigi
99	0.0	1.00	0.0	0.75	0.0	1.0	0.5	0.00	0.00	0.00	...	0.0	0.00	0.00	0.00	0.0	0.0	0.00	0.0	0.75	Gingivitis

100 rows × 29 columns

Figure 3: sample dataset used for dental diagnosis

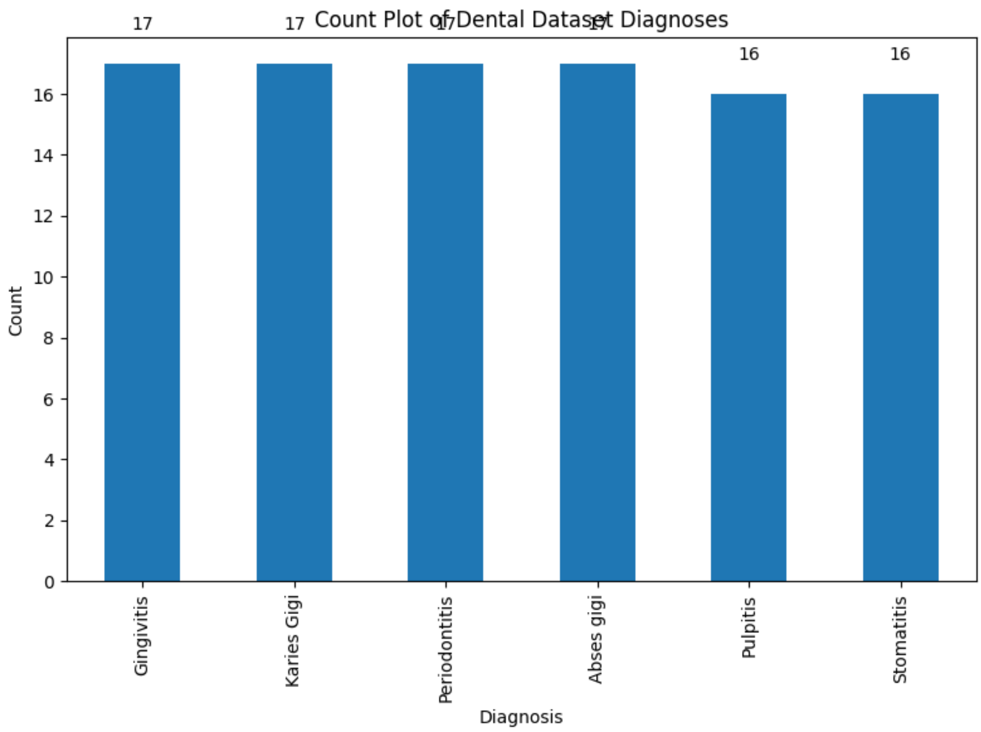

Figure 4: count plot of target column of dataset

```
0        Gingivitis
1        Gingivitis
2       Karies Gigi
3     Periodontitis
4       Karies Gigi
          ...
95         Pulpitis
96    Periodontitis
97       Abses gigi
98      Karies Gigi
99       Gingivitis
Name: Diagnosis, Length: 100, dtype: object
```

Figure 5: Target column of a dataset used for dental diagnosis

```
array([[0.5 , 0.75, 0.5 , ..., 0.  , 0.  , 0.  ],
       [0.  , 0.  , 0.  , ..., 0.  , 0.  , 0.  ],
       [0.  , 0.  , 0.  , ..., 0.  , 0.  , 0.  ],
       ...,
       [0.  , 0.  , 0.  , ..., 0.25, 0.  , 0.  ],
       [0.  , 0.  , 0.  , ..., 0.  , 0.  , 0.  ],
       [0.  , 1.  , 0.  , ..., 0.  , 0.  , 1.  ]])
```

Figure 6: features of dataset after preprocessing

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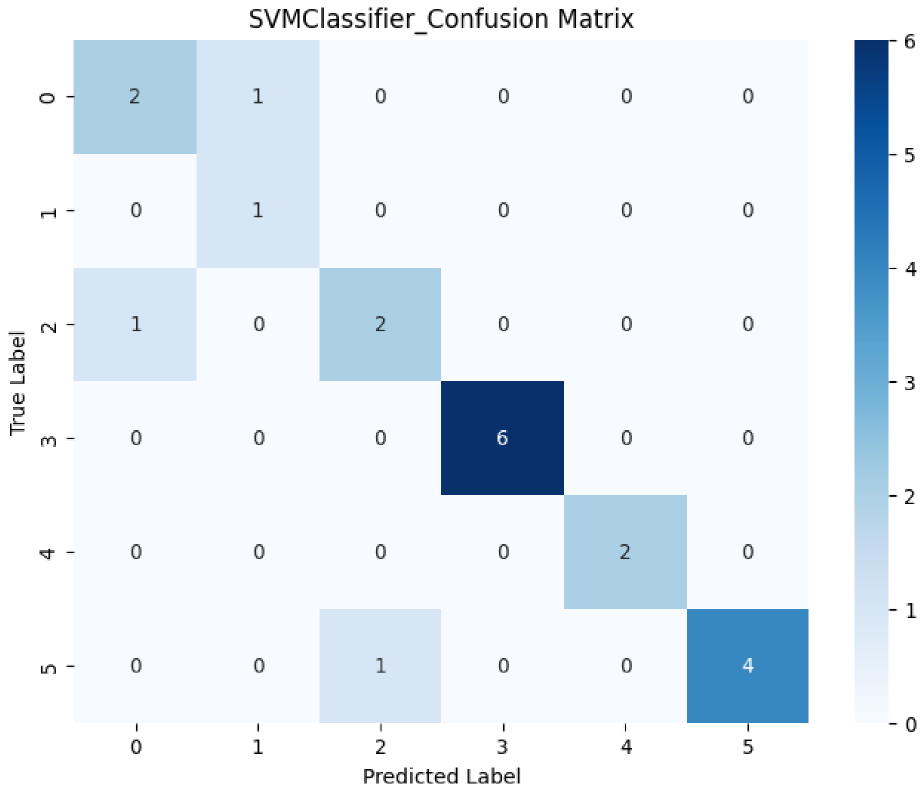

Figure 7: confusion matrix

5. Conclusion

In conclusion, the development of an expert system for enhanced dental disease diagnosis represents a significant step forward in improving the accuracy and efficiency of dental healthcare. By harnessing the capabilities of artificial intelligence, this system has the potential to augment the skills and expertise of dentists, leading to more precise diagnoses, better treatment plans, and ultimately, improved patient outcomes. It addresses the limitations of traditional manual diagnosis, such as human errors and biases, while also providing access to real-time updates from dental research, ensuring that dental professionals stay up to date with the latest advancements in the field. This project underscores the transformative role of AI in healthcare and sets the stage for further innovation in medical diagnostics.

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