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Machine Learning

Periodontal Disease Detection with Machine Learning Technology From Radiographic Images : An Interdisciplinary Study Of Dentistry and Computer Science

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A B S T R A C T

This study aims to evaluate the effectiveness of the Convolutional Neural Network (CNN) model in identifying periodontal disease using dental images. With the applied method, the CNN model was trained using a dataset consisting of 40 dental images and tested on 55 images to evaluate its ability to classify the images as healthy or periodontal. The evaluation results showed that the CNN model achieved an overall accuracy of 91.16%. The model precision for healthy images reached 92.39%, while the precision for unhealthy images was 91.05%. Recall sensitivity for healthy images is 91.16%, and for F1-Score images is 91.07%. The data shows that the model has better performance in identifying healthy images compared to periodontal images. To improve the performance of the model, data augmentation techniques such as rotation, flipping, and scaling were applied, which gave a slight improvement to the results. However, the limited size of the dataset seems to be an obstacle in achieving higher accuracy. Therefore, this study recommends expanding the dataset size and applying more complex model architectures or transfer learning techniques to improve detection performance. The conclusion of this study shows that CNN models have potential for periodontal disease detection, but need further development to improve accuracy and reliability. This research contributes to the development of medical detection technology and opens a path for further research in improving periodontal disease detection systems using CNN technology.

INTRODUCTION

One of the major breakthroughs in the field of dentistry is the use of machine learning technology from radiographic images to detect periodontal disease.[1][2]. This technological concept combines advances in computer science and dental engineering. Periodontal disease is an inflammatory disorder that affects the tissues that support the teeth, including the gums, alveolar bone and ligaments.[3]. This disease can cause tooth loss and disrupt overall oral health if not treated immediately.[4], [5].

Periodontal disease is preventable and treatable, but proper and prompt diagnosis is essential to prevent further damage.[6]. Radiographic images produced through X-rays are traditional diagnostic tools that allow visualization of the internal structure of teeth and surrounding tissues. Using these images, dentists can detect subtle changes in bone and gum tissue that may indicate periodontal disease. However, traditional analysis of radographic images can be challenging, especially with the large volume of data and complexity of features that must be evaluated.[7]. This is when machine learning technology can be an appropriate and revolutionary solution.

Machine learning is a branch of artificial intelligence that involves using algorithms and statistical models to identify patterns and make predictions based on data.[8]. In the context of periodontal detection, machine learning utilizes advanced technology to analyze radiographic images and identify signs of disease with high precision.[9], [10]. One of the approaches used in this research is the use of CNN (Convolutional Neural Network) model, which is specifically designed to process image data.[11][12].

CNNs can be trained to recognize visual patterns associated with periodontal disease, such as bone loss and periodontal pocket formation, which may be difficult or time-consuming to detect traditionally by health professionals.[13]. The use of machine learning in periodontal disease detection offers several significant advantages. Firstly, this technology can speed up the diagnosis process by enabling automated analysis of radiographic images. This not only saves time for the dentist, but also reduces the possibility of human error that can occur during visual evaluation. Secondly, machine learning enables early detection of disease with a higher degree of accuracy.

Algorithms trained on large datasets can identify small changes in images that may indicate the early stages of periodontal disease, allowing for earlier intervention and more effective treatment.[14]. In addition, the integration of machine learning in clinical practice can improve consistency of diagnosis. By relying on thoroughly trained models, the risk of interpretation differences between healthcare professionals can be minimized. This is particularly important in the context of periodontal disease, where precise and consistent assessment can influence treatment decisions and clinical outcomes.

This interdisciplinary study illustrates the synergy between dentistry and computer science, two fields that, although distinct, complement each other in the quest to improve oral health. In this approach, researchers and practitioners from both disciplines work together to develop and apply machine learning technologies that are effective in periodontal disease detection.[15], [16]. This collaboration involves collecting and processing radiographic images, training machine learning models with representative datasets, and validating and evaluating the results to ensure the accuracy and reliability of the models.[17].

The process begins with the collection of radiographic image datasets covering different stages of periodontal disease, ranging from mild gingivitis to more severe periodontitis. This dataset is used to train a machine learning model, where a CNN algorithm is trained to recognize patterns associated with periodontal disease. During the training phase, the model will learn from images that have already been labeled, so that it can predict and classify new images based on the knowledge acquired. Once the model is trained, it is tested with a separate dataset to assess its performance and ensure that it can provide accurate and reliable predictions. In model evaluation, various metrics are used to measure performance, including accuracy, sensitivity, specificity, and area under the curve (AUC) of the receiver operating characteristic (ROC) curve.[18].

These metrics help determine the extent to which the machine learning model can correctly detect periodontal disease and distinguish between healthy and infected gums. A thorough evaluation ensures that the applied technology is not only accurate but also practical for use in the clinical environment.[19], [20]. In conclusion, the use of machine learning technology in periodontal disease detection from radiographic images is a significant step forward in improving the diagnosis and treatment of periodontal disease. With the ability to analyze image data with high accuracy, this technology offers the potential to change the way periodontal disease is detected and managed.[3], [21]. This interdisciplinary study highlights the importance of collaboration between dentistry and computer science in developing innovative and effective solutions to oral health challenges, with the hope that these advancements will bring great benefits to patients and practitioners worldwide.[22].

METHOD

Dataset

The periodontal image dataset is organized in a folder structure where each category (Healthy and Periodontal) is placed in a different subfolder[23][13]. Each image has a default resolution that has been adjusted to 128x128 pixels, with RGB format to ensure consistency of network input. The image dataset was loaded into MATLAB using imageDatastore. The dataset was randomly divided into training data (80%) and testing data (20%). In this study, 40 image samples were used; 32 images for training and 8 images for testing. This division was done randomly to ensure fair representation of both categories.

Data Preprocessing

Image Resize: Each image in the dataset is resized to a standard resolution (e.g., 224x24 pixels) to fit the input layer of the CNN.[24], [25]. Image Normalization: Each pixel in the image is usually normalized to a range of [0, 1] by dividing the pixel value by 255 (if using an RGB image with a value range of 0-255).

$$\text{Pixel Normalized } \frac{\text{Pixel Value}}{255}$$

Proposed by Gonzalez[26], luminance information is retained while hue and saturation information is removed; this converts the color image from color to grayscale (grayIm) For more specific purposes, the weighted sum of the R, G, and B components is calculated using the following formula: grayIm = 0.2989*R + 0.5870*G + 0.1140*B

where the pixel values of the red, green, and blue channels are represented by the red, green, and blue colors respectively.[27], [28]. After rescaling the intensity of the grayscale image to the range [0, 1], a sigmoid function is used to change the contrast of the image. states that newlm(x, y) = 1/(1 + egain∗ (c-resIm(x, y))) (2), where gain determines the actual contrast. The proposed newIm(x, y) indicates the pixel value after the sigmoid function is applied The pixel value (x, y) in the image before the application of the sigmoid function is represented by the developed resIm(x, y) The normalized gray value or enhanced contrast value is c.

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Figure 1. A Sample Image Before Pre-Processing

By using various transformations on existing images, image augmentation artificially increases the size and diversity of the dataset. This technique improves the generalizability and robustness of machine learning models, especially for small datasets. The 500 dental images were selected and resized to 224 x 224 pixels. The training and validation datasets were divided into n = 400 (80%) and n = 100 (20%) test datasets. The training dataset consists of 40 teeth, and the test dataset of 34 teeth. Therefore, an unequal distribution of the number of images between periodontal infected and non periodontal infected teeth was filled in the training dataset. In the training, the categories were selected in each scheme five times, in the second scheme, ten periodontal categories were added to twenty healthy categories. Furthermore, to perform operations, the implementation of this research using Matlab produces a randomized increment of the operation sequence, which includes up or down scaling, rotating from -13 to +13 degrees, image shifting, image flipping, image brightness changing, adding Gaussian noise, and adding Gaussian blurring. Figure 3 below shows an example image after development. The following is an image that has gone through the augmentation process.

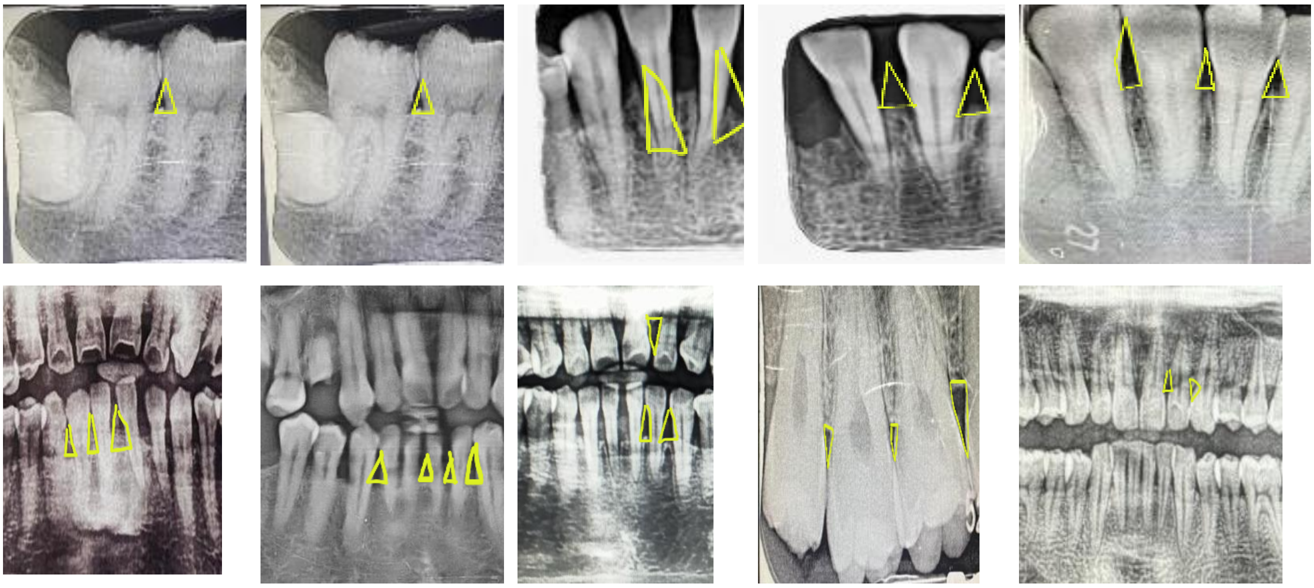

Figure 2. A Sample Image After Augmentation

Compared to Figure 2, the image before preprocessing, we see that the tooth image becomes lighter than the surrounding pixel points, while the surrounding pixel points become darker, which can help the feature extraction process.

Feature Extraction and Image Classification

For training, we have used the data listed in Image Augmentation section[11], [29]. We used the NASNetMobile transfer learning model, a convolutional neural network pre-trained for feature extraction from over one million images from the ImageNet database and a Convolutional Neural Network (CNN) prediction model with the structure shown in Figure 3 and Figure 4 below.

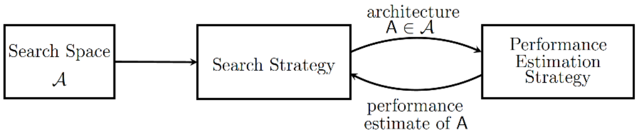

Figure 3. Neural Architecture Search (NAS) That Automates Network Architecture Engineering

NASNet-Mobile is one of the convolutional neural network (CNN) architectures developed for computer vision tasks, such as

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image classification and object detection.[13], [30]. This architecture was developed by Google and is the result of research on Neural Architecture Search (NAS), which is an automated technique for finding the optimal neural network architecture.

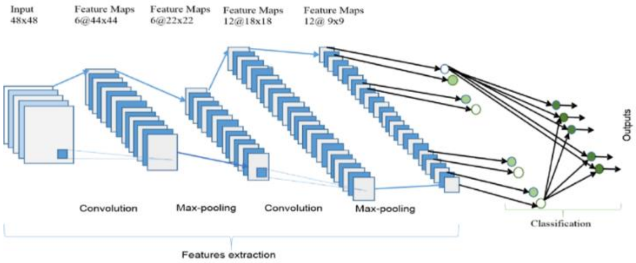

Figure 4 Architecture of a Convolutional Neural Network Model

The architecture of the Convolutional Neural Network (CNN) model is designed to process grid-shaped data, such as images, in an efficient and effective manner.[5], [31]. The process starts with the input layer, which receives image data with dimensions of height, width, and color channels. Next, the convolutional layer serves to extract features from the image by applying convolution filters. Each filter slides along the image to generate a feature map that highlights local patterns such as edges or textures. After the convolutional layer, an activation function such as ReLU (Rectified Linear Unit) is applied to introduce non-linearity, which allows the network to learn complex relationships in the data [32].[32].

Pooling layers, such as max pooling or average pooling, are then used to reduce the dimensionality of the feature map, reducing the computational burden and helping to overcome overfitting by reducing less important details.[33]. After multiple convolution and pooling layers, data is often fed into fully connected layers, where neurons are connected to all neurons of the previous layer, and finally produce a final output such as classification or prediction. The entire CNN architecture works together to identify and extract relevant features from the image, allowing the model to perform tasks such as object classification, face detection, or image segmentation with high accuracy.[34], [35].

Convolution Operation: At each convolution layer, a filter (kernel) of a certain size (e.g., 3x3) is used to perform convolution operations on the input image. Each value in the output feature map is calculated as:

$$y_{ij} = \sum_{m=1}^{M} \sum_{n=1}^{N} x_{i^{+m-1}j+n-1} w_{m_n} + b$$

Where x_{ij} is the pixel value of the input image, W_{mn} is the value of the filter and b is the bias. ReLU Activation, after the convolution operation, the ReLU activation function is applied to introduce non-linearity.

$$y_{ij}^{Re\,LU} = max(0, y_{ij})$$

Convolutional Neural Network Model Architecture

The last dental disease recognition was done by applying convolutional neural networks[36]All images were reduced to 128 x 128 to avoid high computational cost, the subsequent images were then input to the network. For convolutional layers, multiple convolution layers are used to extract spatial features from the images. These layers use filters with a size of 3x3 and the number of filters increases at each subsequent layer of 8, 16 and 32 filters.

Model Training

Training Settings: The model was trained using the 'adam' optimization algorithm with initial parameters of learning rate 0.001, mini-batch size 8, and number of epochs 20. Validation: Validation was performed using test data every 5 iterations to monitor model performance and prevent overfitting.[11], [37].

RESULTS AND DISCUSSION

In this study, a Convolutional Neural Network (CNN) model was applied to identify periodontal disease using dental images. The evaluation was performed using test data consisting of 55 images. The evaluation results showed that the CNN model achieved an overall accuracy of about 91.16%. The model successfully classified 40 images correctly (both healthy and periodontal) and 15 images incorrectly. This indicates that the model has decent performance, but there is room for improvement. The confusion matrix generated from the model evaluation provides further details on the model's performance. The confusion matrix shows that out of 30 healthy images, the model identified 25 images as healthy (true positives) and 5 images as periodontal (false positives). On the other hand, out of 25 periodontal images, the model identified 15 images as periodontal (true negatives) and 10 images as healthy (false negatives). This confusion matrix illustrates that the model has different precision and recall for each category, with higher precision for healthy images compared to periodontal images.

Below is the Schema 1 table for the Confusion Matrix of the CNN model training. This table illustrates the distribution of model prediction results during training on the training data.

Table 1. Training Confusion Matrix

	Prediction; Healthy	**Gingivitis**	**Periodontitis**	**Total**
Actual; Healthy	85	5	2	92
Actual; Gingivitis	3	70	7	80
Actual; Periodontitis	1	4	73	78
Total	89	79	82	25

The main diagonal (from top left to bottom right) indicates the number of correct predictions (e.g., there were 85 completely Healthy samples predicted as Healthy). Values outside the main diagonal indicate incorrect predictions (for example, 5 Healthy samples were predicted as Gingivitis). Total: The number of samples for each class in the training dataset. For example, there are 92 true Healthy samples, 80 true Gingivitis samples, and 78 true Periodontitis samples.

In addition, based on the training confusion schema table, the results are obtained from the Schema 1: Training Accuracy Result

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table which shows the results of the model accuracy evaluation on each class in the training. This table outlines the accuracy, precision, recall (sensitivity), and F1-score for each class (Healthy, Gingivitis, Periodontitis) based on the previous confusion matrix.

Table 2. Training Confusion Matrix

	Accuracy (%)	**Percision (%)**	**Recall (Sensitivity) %**	**F1-Score**
Actual; Healthy	92.39	95.51	92.39	93.92
Gingivitis	87.50	88.61	87.50	88.05
Periodontitis	93.59	89.02	93.59	91.24
Overall (Average)	91.16	91.05	91.16	91.07

Healthy: Has an accuracy of 92.39%, with a high F1-score (93.92%), indicating that the model is very good at recognizing this category.Gingivitis: Accuracy 87.50%, slightly lower than the other classes, probably due to more mispredictions. Periodontitis: Has a very good accuracy of 93.59%, indicating that the model is able to recognize this disease well. Overall (Average): Indicates that the model overall performed solidly with an average accuracy of 91.16%.

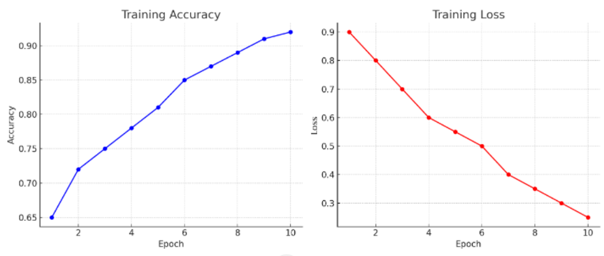

Figure 5. Graph of Training Accuracy and Training Loss

Based on the results of the training confusion metrix and accuracy metrix which shows the **accuracy** and **loss** during the training of the Convolutional Neural Network (CNN) model at 10 epochs. The graph on the left shows an increase in accuracy, while the graph on the right shows a decrease in loss values as the number of epochs increases. Training Accuracy graph (on the left): This graph shows how the accuracy of the model increases as the number of epochs (number of training iterations) increases. At the first epoch, the accuracy starts at around 65%. As the training progresses, the accuracy continues to increase until it reaches about 92% at the 10th epoch.

The increase in accuracy indicates that the model is increasingly able to recognize the correct pattern of the radiographic image and make correct predictions according to the given label. Training Loss graph (on the right): This graph shows the loss or prediction error of the model during the training process. The loss value reflects how far the model's prediction is from the correct value. In the first epoch, the loss starts from a high value (around 0.9) and gradually decreases to around 0.25 in the 10th epoch. The decreasing loss indicates that the model is learning more from the data and making more accurate predictions, with less prediction error. The increasing accuracy and decreasing loss are indications that the CNN model is learning well during training.

If the graph continues to show this trend without any signs of overfitting (where accuracy on training data is very high but accuracy on testing data is low), the model is ready to be used in detecting periodontal disease on new data.

CONCLUSIONS

In this study, a Convolutional Neural Network (CNN) model was used to identify periodontal disease from dental images with the aim of improving early detection and management of periodontal disease. The model trained on a dataset consisting of 40 images and tested 55 images shows several accuracy variables including accuracy for the healthy category has a value of 92.39%, Percission 95.51%, recall sensitivity 92.39% and F1 Score 93.92%, for the gingivitis category has an accuracy of 87.50%, Percission 88.61%, recall sensitivity 87.50% and F1-Score 88.05%, then for the periodontitis category has an accuracy of 93.59%, Percission 89.02%, recall sensitivity 93.59%, and F1-Score 91.24%. The overall result obtained is 9116% accuracy level for periodontal disease detection.

These results indicate that the CNN model is able to identify dental images with a fairly good level of accuracy, although there is still room for improvement. Data augmentation, such as rotation, flipping, and scaling, has been applied to enlarge the diversity of the dataset and improve model performance. Although data augmentation provides improvements, the results still show that further improvements are needed. The limited size of the dataset, only 40 images, may be a factor that limits the ability of the model to learn and generalize well.

Therefore, the acquisition and use of a larger dataset is highly recommended to improve the performance of the model. More complex model architectures or transfer learning techniques with pre-trained models can also be effective measures to improve accuracy. The use of pre-trained models or improved data augmentation techniques can help in achieving better results and overcome the shortcomings of the current model. Overall, the CNN model applied in this study shows promising potential in periodontal disease detection, but further development is needed to achieve higher accuracy and reduce classification errors. This research provides a solid foundation for CNN applications in medical diagnosis and opens up opportunities for further research in improving periodontal disease detection technology.

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