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AUTOMATIC CLASSIFICATION SYSTEM FOR PERIAPICAL LESIONS WITH THE TOOTHNET CNN ARCHITECTURE INTEGRATING THE PROPOSED HYBRID ACTIVATION FUNCTION ON CBCT SCANS

CBCT TARAMALARINDA ÖNERILEN HIBRIT AKTIVASYON FONKSIYONUNU ENTEGRE EDEN TOOTHNET CNN MIMARISI ILE PERIAPIKAL LEZYONLAR IÇIN OTOMATIK SINIFLANDIRMA SISTEMI

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ABSTRACT

Imaging techniques are widely used in dentistry to understand the 3D structure of teeth and detect diseases, but their interpretation is time-consuming and prone to error. To address this, decision support systems are increasingly utilized. This study proposes a CNN-based classification model using the UFPE dataset, which includes Cone Beam Computed Tomography (CBCT) scans. In the first scenario, both real and enhanced images were input into a CNN, yielding 68.92% accuracy for enhanced images. Due to a result, enhanced images were used in all other scenarios. In the second scenario, a newly designed CNN architecture called ToothNet, incorporating a custom activation function, was tested. It achieved 69.92% accuracy, 61.45% recall, 62.67% precision, and 68.68% F1-score, showing a 1.45% increase in accuracy. To evaluate generalizability, three more classification scenarios were examined using the same dataset. ToothNet achieved 80.14% accuracy in the “healthy vs. large lesion” and 68.73% in the “healthy vs. small lesion” classification. These results indicate that the proposed architecture not only improves accuracy but is also generalizable across different lesion sizes.

Keywords: CBCT imaging approach, original image processing method, toothnet CNN architecture, proposed hybrid activation function, classification of normal and lesion images.

ÖZET

Görüntüleme teknikleri, dişlerin 3 boyutlu yapısını anlamak ve hastalıkları tespit etmek için diş hekimliğinde yaygın olarak kullanılmaktadır, ancak bunların yorumlanması zaman alıcıdır ve hataya açıktır. Bu sorunu çözmek için karar destek sistemleri giderek daha fazla kullanılmaktadır. Bu çalışma, Konik Işınlı Bilgisayarlı Tomografi (CBCT) taramalarını içeren UFPE veri setini kullanan CNN tabanlı bir sınıflandırma modeli önermektedir. İlk senaryoda, hem gerçek hem de geliştirilmiş görüntüler bir CNN'ye girildi ve geliştirilmiş görüntüler için %68,92 doğruluk oranı elde edildi. Bu iyileştirme nedeniyle, diğer tüm senaryolarda geliştirilmiş görüntüler kullanıldı. İkinci senaryoda, özel bir aktivasyon fonksiyonu içeren, ToothNet adlı yeni tasarlanmış bir CNN mimarisi test edildi. Bu mimari %69,92 doğruluk, %61,45 geri çağırma, %62,67 kesinlik ve %68,68 F1 puanı elde ederek %1,45 doğruluk artışı gösterdi. Genelleştirilebilirliği değerlendirmek için, aynı veri seti kullanılarak üç sınıflandırma senaryosu daha incelendi. ToothNet, “sağlıklı vs. büyük lezyon” sınıflandırmasında %80,14 doğruluk ve “sağlıklı vs. küçük lezyon” sınıflandırmasında %68,73 doğruluk elde etti. Bu sonuçlar, önerilen mimarinin sadece doğruluğu artırmakla kalmayıp, farklı lezyon boyutları arasında da genelleştirilebilir olduğunu göstermektedir.

Anahtar Kelimeler: CBCT görüntüleme yaklaşımı, orijinal görüntü işleme yöntemi, toothnet cnn mimarisi, önerilen hibrit aktivasyon fonksiyonu, normal ve lezyon görüntülerinin sınıflandırılması

INTRODUCTION

The effectiveness of diagnostic and treatment processes in dentistry is highly dependent on accurate and detailed imaging techniques. Imaging methods used to obtain information about the structural integrity and health of teeth play a critical role in the process of diagnosing and creating treatment plans. Therefore, coronal and sagittal sections, which are among the dental imaging techniques, have an important functionality for clinical applications (Benington et al., 2010).

Coronal sections allow a detailed examination of the anterior surfaces and posterior regions of the teeth, while sagittal sections depict the lateral cross-sections and details of the internal structures of the teeth. These sections are used to understand the three-dimensional structure of teeth and provide important information for the diagnosis of dental diseases (Patel et al., 2019). In particular, advanced imaging techniques such as dental tomography and magnetic resonance imaging are often preferred to obtain such cross-sections. However, analyzing such conventional imaging methods is often a time-consuming and complex process. Manual review of images can lead to both a high risk of error and time loss. Due to these difficulties, image processing and artificial intelligence-based detection methods in the IT world have gained an important place in the field of dentistry as decision support systems. In particular, convolutional neural networks (CNNs), a subset of the artificial intelligence framework, are one of the most common methods that exhibit superior performance in recognizing and classifying patterns in image data (LeCun et al., 2015). CNN architectures, which obtain meaningful, powerful, and abstract representations by automatic feature extraction from images, offer successful outputs in object detection and image recognition tasks. However, applying image processing methods to the data to be fed as input to the CNN structure has the ability to increase the training potential (Akalın & Yumuşak, 2024). Image processing techniques offer a wide set of tools to improve the quality of dental images and enhance the analysis processes. These techniques can make the structural features of teeth more prominent through various functionalities applied to the images. For example, methods such as histogram equalization, edge detection, and noise removal are used to highlight important details and detect abnormalities in dental images (Chauhan et al., 2023). On the other hand, the entropy curve measures the information in an image and helps to highlight important details (Rajinikanth et al., 2017). Computing the edge and corner points in the image to reveal its structural details is another approach used to improve performance (Akalın & Yumuşak, 2024). Improving visual perception by adjusting the color channel (RGB) values with linear transformations (Mohammed et al., 2022), applying an algorithm to transform from RGB space to LMS wavelengths to provide better perception, or improving image quality by contrast enhancement, blurring, K-Means color clustering, and thresholding are functionalities applied to images (Rathee & Mann, 2022). In addition, hybrid use of existing image processing methods or translation to different color spaces are critical moves in improving performance (Akalın & Orhan, 2024). Through these processes, more meaningful and informative input data and optimization of learning processes are provided (Rajinikanth et al., 2017). As a result of increasing the efficiency of image processing processes, it is possible to make more accurate diagnoses within the scope of clinical applications.

CNN architectures, in which enhanced images are given as input during the construction of the decision support system, obtain meaningful, powerful, and abstract representations by automatic feature extraction from images. In addition, applying image processing methods to the data to be fed as input to the CNN structure has the ability to increase the learning potential of the network (Akalın & Yumuşak, 2024). CNNs have high capabilities in automatically processing and analyzing images, using multilayer structures to learn features from images and detecting different features at each layer. The use of CNNs in the classification of coronal and sagittal slices in enhanced dental images is valuable for automatically identifying and analyzing the target input (Krizhevsky et al., 2012; Akalın & Yumuşak, 2024). Therefore, CNN and image processing methods have emerged as important approaches in the diagnosis of dental diseases, detection of lesions, and general dental health assessments (Schwendicke et al., 2019). They also have the power to improve overall clinical efficiency by reducing physician errors and time loss. The main motivation for the study is explained as follows in the work of Akalin, F., & Yildiz, T., 2025. The process of taking dental X-rays is shaped by the patient remaining still. However, depending on the patient's specific condition, this imaging process has the potential to be negatively affected. For such situations, image processing is important for detecting the image with maximum performance. On the other hand, deep learning-based CNN architectures build decision support systems by automatically extracting features from images. The developed decision support systems enable the reduction of false decision rates through fine-tuning.

In this article, a study on the classification of small lesions, large lesions, and healthy categories on a dataset consisting of coronal and sagittal slices was conducted. In the first stage, image processing methods were used to reveal sensitive and critical points in the images. In the second stage, optimized images obtained by applying a suitable combination of image processing approaches were fed into the designed CNN architecture as input. As a result of the classification process for images with and without lesions, 92.6% and 93.5% accuracy rates were obtained on the original and optimized images, respectively. Therefore, in the next step, the enhanced images with and without lesion categories were classified using a new hierarchical scheme in which the proposed activation function was integrated into the designed ToothNet CNN architecture. Performance metrics of 69.92%, 61.45%, 62.67%, and 68.68% were obtained for accuracy, recall, precision, and F1 Score, respectively.

LİTERATURE REVİEW

In dentistry, various methods and technologies are used to analyze dental images in order to improve diagnosis and treatment processes. In particular, computed tomography (CT) is a traditional imaging method that offers the potential to be preferred due to its ability to visualize the three-dimensional structure of the teeth in detail (Calazans et al., 2022). Various studies on CT imaging methods have been conducted in the literature.

Experiments with various deep learning architectures on a large dataset collected from two university hospitals in Germany and India for the classification of dental radiographs and automatic detection and classification of dental diseases have shown that the application of data augmentation and preprocessing techniques can achieve accuracy rates of over 90% (Cejudo et al., 2021). The effect of convolutional neural networks (CNNs) in dental imaging has also been evaluated by analyzing datasets obtained from cone-beam computed tomography (CBCT) and radiographs using different CNN architectures, showing that CNNs can achieve higher accuracy rates than traditional methods, with an overall success rate of around 85% (Schwendicke et al., 2019). Using a small dataset of 251 images labeled by dentists and radiologists, CNN and transfer learning methods achieved 90% accuracy and 85% precision, highlighting the advantage of transfer learning in diagnosing dental diseases (Prajapati et al., 2017). Deep neural networks (DNNs) have also been used to classify periapical dental X-ray images from a dataset of 16,000 images, where data augmentation and transfer learning techniques produced an accuracy rate of 85% (Vasdev et al., 2022). In the classification of dental caries, a CNN-based model trained on the teeth_dataset achieved 88% accuracy and 86% precision after applying image enhancement and preprocessing methods (Sonavane et al., 2021). Similarly, CNN architectures applied to a dataset labeled by dentists identified different types of caries with 91% accuracy and 89% precision (Megalan Leo & Kalpalatha Reddy, 2020). An anonymized CBCT dataset collected between 2020 and 2023 for dental caries detection and classification produced accuracy rates above 96% (Esmaeilyfard et al., 2024). Enhanced dental caries classification in CBCT images using image processing and self-supervised learning achieved 90% accuracy (Zanini et al., 2024). Training CNN models on CT datasets from Veraviewepocs 3D and Alphard VEGA dental CT units for automatic tooth identification resulted in accuracy rates over 88% (Miki et al., 2017). Automatic segmentation of tooth roots from CBCT images achieved 93% accuracy (Ma & Yang, 2019). CNN-based segmentation of dental implants in CBCT scans produced more than 95% success (Lee et al., 2020). Deep learning-based segmentation of oral lesions from CBCT images reached 98.3% accuracy (Wang et al., 2021).CBCT images from the UFPE dataset were used for automatic classification of periapical lesions, achieving over 81% accuracy with transfer learning models (Calazans et al., 2022). Lesion categorization based on a radiographic periapical index scoring system achieved over 92% accuracy using CNNs (Moidu et al., 2022). The current state and future directions of imaging techniques for detecting periapical lesions have been reviewed, comparing classical and modern methods and emphasizing the potential of machine learning and artificial intelligence applications in lesion detection (Cotti & Schirru, 2022).

These studies contribute significantly to improving dental health and optimizing treatment processes, while also demonstrating the strong applicability of deep learning methods in dentistry.

MATERIAL AND METHOD

Digital images are data sources containing valuable information. Image processing methods are widely used to extract sensitive and critical information from these sources. Image processing refers to the techniques used to analyze and enhance digital images. It involves converting encoded images into image matrices after decoding, followed by optimization, transformation, filtering, and similar operations applied to these matrices (Aksoylu, 2021).

In recent years, the use of artificial intelligence techniques in the field of medical digital imaging has significantly transformed diagnosis and treatment processes. Due to their ability to analyze large datasets, artificial intelligence algorithms can evaluate images more quickly and accurately, thereby supporting clinical decision-making. Moreover, deep learning methods have demonstrated remarkable success in automatically detecting, classifying, and measuring lesions in medical images (Ronneberger et al., 2015). These developments not only facilitate the early diagnosis of diseases but also improve the efficiency of healthcare services and reduce the workload of physicians. In this direction, combining medical image processing with deep learning-based techniques aims to produce outputs with high accuracy and reliability.

In this section, a novel methodology is presented to achieve successful classification of coronal and sagittal lesion types in the dental region. Accordingly, the dataset used in the study, the developed image processing filter, the classification process, and the proposed activation function are described below.

Dataset

The dataset used in this study was reviewed and approved by the Local Research Ethics Committee of the University of Pernambuco in Brazil. It consists of two categories: healthy and unhealthy. It consists of 1,000 Cone Beam Computed Tomography (CBCT) dental scans. Each sample in this dataset, named UFPE, is organized as a pair of images in the coronal and sagittal planes (Calazans et al., 2022). The dataset, which contains a total of 2000 different images, allows for a more accurate assessment of lesions in clinical applications. Therefore, the dataset is a valuable resource for both researchers and clinical practice. Sample images of tooth sections with lesions, small lesions and no lesions, and their expressions are presented in Figure 1.

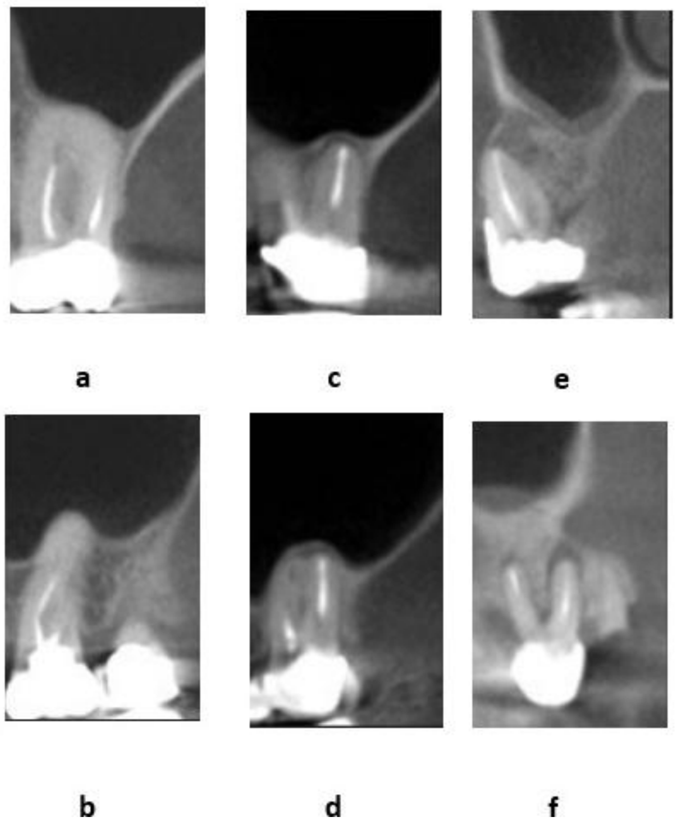

Figure 1. Examples of images in the sagittal and coronal planes of the UFPE dataset.

Images labeled a and b in Figure 1 are examples without lesions and represent coronal and sagittal slices, respectively. Images labeled c and d represent small lesions and represent coronal and sagittal slices, respectively. Images labeled with e and f represent large lesions and represent coronal and sagittal slices, respectively. Table 1 provides a summary of the dataset used in this study.

The original and enhanced 2000 images used in the study were used with their native resolution (186 × 115). For the classification task, the dataset was first divided into 80% training and 20% test sets using stratified sampling to ensure equal class distribution across both subsets. Furthermore, 20% of the training set was internally separated as a validation set and used for hyperparameter tuning and model optimization. Early stopping was applied during training to prevent overfitting and to ensure stable convergence.

Table 1. Summary of the UFPE dataset (Calazans et al., 2022).

Classification	Number of Samples (Coronal and Sagittal)	Features
Without lesion	898	Teeth without lesion
Large lesion	542	Teeth with lesion of 2.0 mm or greater
Small lesion	560	Teeth with lesion of 0.5 to 1.9 mm

Model Development

In recent years, the field of medical imaging has made great progress with the use of artificial intelligence (AI) techniques. These developments have led to significant changes in the analysis and classification of medical images. In particular, deep learning-based convolutional neural networks designed for analysis and classification processes produce effective outputs (LeCun et al., 2015).

Deep learning offers three main advantages in the evaluation of medical images. The first advantage is that it empowers clinical decision support systems by providing high accuracy and reliability on large datasets (Esteva et al., 2017). The second advantage is the realization of automatic feature extraction (Krizhevsky et al., 2012). The third advantage is its potential to be effective even in the diagnosis of different diseases due to its increasing generalization capacity, enabled by training on large and diverse medical image datasets (Rawat & Wang, 2017). In addition to these advantages, the impact of deep learning-based algorithms has been observed in critical areas such as medical imaging, cancer diagnosis, disease classification, and anomaly detection. It is preferred because it has the potential to accelerate early diagnosis and treatment processes, and its high accuracy in morphological and functional analysis of medical images (Litjens et al., 2017) helps increase reliability in clinical applications.

The model development process built using the deep learning approach, which is a subfield of the artificial intelligence framework, includes four basic stages for efficient classification of medical images. These stages are: the developed image processing approach, architecture design, integration of the proposed activation function into the designed CNN architecture, and evaluation. The first three stages have the potential to directly impact the overall performance of the model. In particular, improving the data quality significantly enhances the generalization ability and accuracy of the model (He et al., 2016). For this reason, the images are improved using an image processing approach.

Image Processing

Image processing performs information extraction by performing various functionalities on digital images. The basic functionalities are actions to organize, analyze, and enhance images. It performs manipulations on images. Brightness and contrast adjustments, color correction and balancing, noise reduction, edge detection and boundary detection, filters and masking, morphological operations, and image fusion are some of the functionalities used in image processing (Gonzalez & Woods, 2014; Esteva et al., 2017).

It is important to use these functionalities used in the image processing process in a hybrid order in line with the originality added through different combinations in order to clarify critical points. Because it is not possible to improve the discrimination of lesions in images by applying existing methods sequentially and randomly. For example, while the edge detection algorithm provides an important functionality in finding lesion boundaries, saturation or brightness is valuable for distinguishing lesion differences. Evaluating these two approaches together helps provide more optimized inferences in lesion detection. Therefore, a novel methodology was improved to clarify the boundaries of the relevant regions in the categories of healthy, small lesion, and large lesion. The flowchart of this methodology is given in Figure 2.

In the flow diagram shown in Figure 2, median blur, weighted summation, automatic edge detection, “xor” logical operation, saturation and brightness enhancement, and “and” logical operation were applied to the original images to obtain the final image. Thus, it has been possible to reveal lesions with the potential to create differences in tissue using appropriately combined image processing functionalities. In the last stage, the images whose details were clarified were saved for classification with the custom CNN architecture.

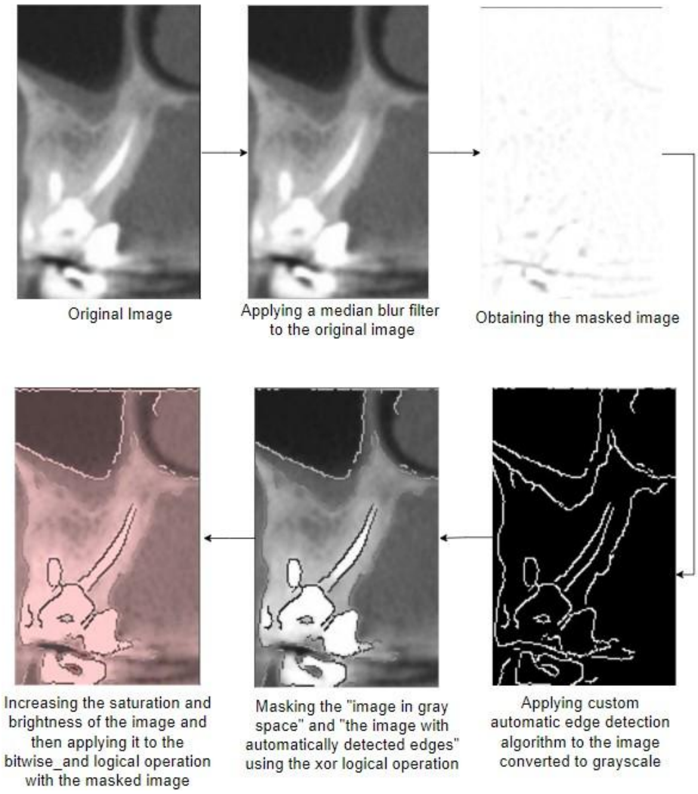

Figure 2. Flowchart of the proposed image processing approach

ToothNet CNN Architecture

Deep learning, a critical component of artificial intelligence, has gained importance in both academic and industrial fields with its remarkable achievements in recent years. Multilayer neural networks are more effective and efficient than traditional machine learning methods due to their ability to extract highly abstract representations and features from complex datasets. These developments have expanded the potential and application areas of deep learning.
Convolutional neural networks (CNNs) are a specialized deep learning architecture. One of the reasons CNNs are often preferred is that the feature extraction process can be performed automatically without human intervention, making them particularly effective for image analysis (Ozkan & Erdogmus, 2024).
The CNN architecture developed in this study, named ToothNet, consists of 31 layers with a total of 469.721 trainable parameters. Single-channel (grayscale) images of size 186×115 are given as input to this architecture. The model begins with an input layer to process the image data. This is followed by convolutional layers, which are the main components of the model.

The first convolutional block contains two consecutive 3×3 convolution filters (Conv2D), both activated by the ReLU (Rectified Linear Unit) activation function (Nair & Hinton, 2010). ReLU allows the model to learn nonlinear relationships and accelerates the learning process. After the convolutional layers, Batch Normalization is applied to support faster and more stable learning by normalizing the data in each mini-batch (Ioffe & Szegedy, 2015). This block is completed with a MaxPooling2D layer, which reduces computational load by downsampling the feature maps while preserving important features (Scherer et al., 2010), and a Dropout layer, which disables random neurons to prevent overfitting (Srivastava et al., 2014). In this model, dropout is set to 0.3.

The second convolutional block focuses on learning deeper features using 16 filters and includes two 3×3 convolution layers, Batch Normalization, MaxPooling2D, and Dropout. This structure increases the model's feature learning capacity and its ability to recognize more complex patterns. Similarly, the third and fourth convolutional blocks use

32 and 64 filters, respectively, increasing the network depth and enabling the learning of more abstract representations.

After the convolutional layers, the Flatten layer transforms the two-dimensional feature maps into a one-dimensional vector. Two fully connected (Dense) layers follow, containing 64 and 32 neurons, respectively. The number of neurons directly relates to the model's learning capacity and complexity. Each neuron's output is passed through the ReLU activation function to allow the network to learn non-linear relationships (Hayou et al., 2019). Batch Normalization and Dropout are again applied sequentially to improve stability and prevent overfitting.

Finally, since both 2-class (with/without lesion) and 3-class (large lesion/small lesion/without lesion) classification tasks are considered, Dense layers with 2 and 3 neurons are created according to the specific classification scenario. In the output layer, the performance of the model is tested using Softmax, tanh, ReLU, and sigmoid activation functions, in addition to the proposed activation function integrated into the CNN architecture named ToothNet. The design of the ToothNet model is illustrated in Figure 3. In addition, the general hyperparameters used during the training of the ToothNet model are summarized in Table 2.

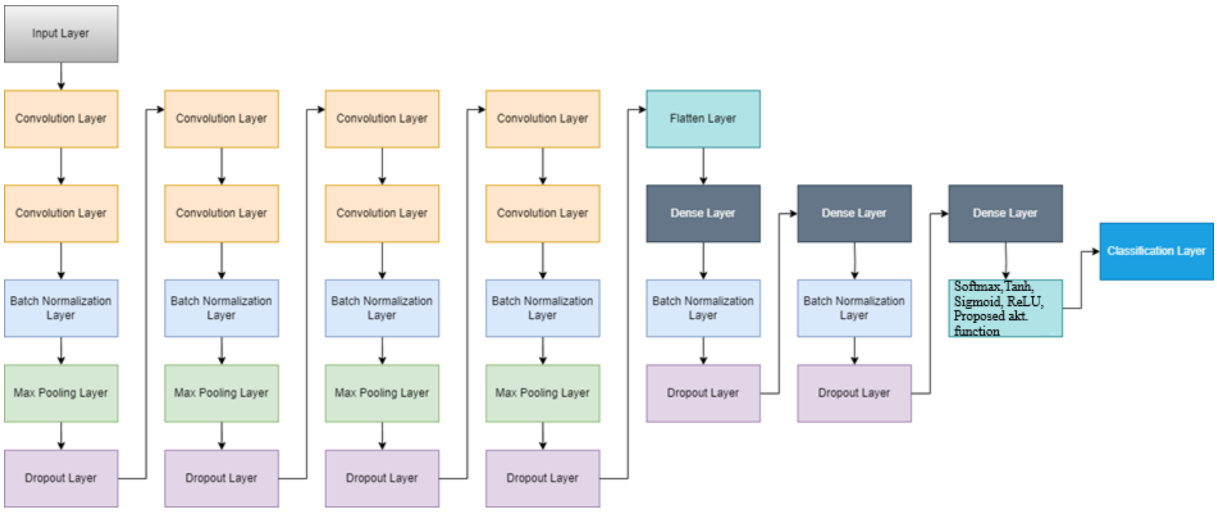

Figure 3. Design of the created ToothNet architecture

Table 2. General training hyperparameters used for the ToothNet model

Hyperparameter	Value
Input Size	186 × 115
Batch Size	32-64
Epochs	150
Optimizer	Adam
Learning Rate	0.001
Dropout Rate	0.3
Activation Functions Tested	ReLU, Sigmoid, Tanh, Softmax, Proposed ToothNet Activation
Early Stopping	Yes
Total Trainable Parameters	469.721

The ToothNet architecture is trained using Softmax, tanh, ReLU, sigmoid and the proposed activation function, and their performances are comparatively evaluated. Then, the effects of different activation functions on the classification performance of the model are analyzed. The ToothNet architecture is a structure created for the model to effectively learn the features of medical images and classify them with high accuracy.

Activation Functions

Activation functions are mathematical expressions that determine the output value of each neuron in artificial neural networks and enable the network to model non-linear relationships. These functions increase the learning capacity of the model on complex data and allow the network to learn more deeply. The choice of activation function plays a critical role in the success of neural networks and should therefore be carefully selected according to the requirements of the application (Goodfellow et al., 2016).

Activation functions are hyperparameters used in both hidden layers and fully connected layers. The activation functions used in the fully connected layers also play a critical role in obtaining the final output of the neural network and determining model performance. The activation function chosen determines how the network output is interpreted and for which types of problems it is suitable. For example, sigmoid and softmax activation functions are typically used for binary and multi-class classification problems, respectively. Activation functions such as Tanh, ReLU, Leaky ReLU, and Exponential Linear Unit are also preferred in intermediate layers (Nair & Hinton, 2010). Optimizing the activation function is crucial for interpreting the outputs of the model, as it provides the most appropriate mapping between input and output.

In this study, an improvement was made in the activation function used in the last layer of the network. All steps for this optimization are detailed under the Proposed Activation Function.

Proposed Activation Function

Sigmoid and softmax activation functions are commonly used in the last layer of the network to interpret outputs. Since they are located in the output layer, they contribute to learning global features. They also have great potential to improve classification performance, produce more stable results, and provide generalizable outputs. In this context, we were inspired by the general structure of the activation function proposed by Akalın & Orhan (2024) to ensure stability and robustness.

In developing the proposed activation function, the FeLU activation function described by Qiumei et al. (2019) was used in addition to the well-known sigmoid, softmax, and swish activation functions. The mathematical expressions for these activation functions are given as: sigmoid in Equation 1, softmax in Equation 2, swish in Equation 3, and FeLU in Equation 4 (Rasamoelina et al., 2020).

$$Sigmoid = \frac{1}{1+e^{-x}} \tag{1}$$

$$Softmax(x_i) = \frac{e^{(x_i)}}{\sum_{j=1}^{n} e^{(x_j)}} \tag{2}$$

$$Swish = \frac{x}{1+e^{-x}} \tag{3}$$

$$FELU(x) = \begin{cases} x & x>0 \\ a(2^{x/\ln(2)} - 1) & x\leq 0 \end{cases} \tag{4}$$

The sigmoid activation function was developed for binary classification problems, while the softmax activation function is suitable for multiclass classification problems. The swish activation function is an adaptive structure derived from the sigmoid activation function, allowing the input to be dynamically modified by the sigmoid (Rasamoelina et al., 2020). The FeLU activation function introduces a new exponential function for the negative parts; its curve has no sharp corners or abrupt changes and possesses a derivative at every point. These properties help to produce more successful and efficient outputs compared to the linear function. The FeLU activation function combines the advantages of Rectified Linear Unit (ReLU) and Exponential Linear Unit (ELU) functions, which reduces the overall running time in neural network architectures (Qiumei et al., 2019).

Optimizing the FeLU activation function is the first step in developing the proposed activation function. In this direction, the aim is to distribute the input values within a smaller range over a larger period and then reduce the influence of large values, allowing the neural network to learn more stably. This approach reduces gradient loss, ensures stable training, promotes a generalizable model, and decreases the risk of overfitting or underfitting. The mathematical expression of the updated FeLU activation function to implement these objectives is shown in Equation 5.

$$Updated\ FELU(x)) = \begin{cases} \log(x) & if\ x>0 \\ a.(2^{\frac{x}{log_{10}^{(2)}}} - 1) & x\leq 0 \end{cases} \tag{5}$$

In Equation 5, the speed of propagation between log(x) in the updated FELU equation and x in the original FELU activation function equation for the x>0 condition is analyzed. A depiction of this situation is given in Figure 4.

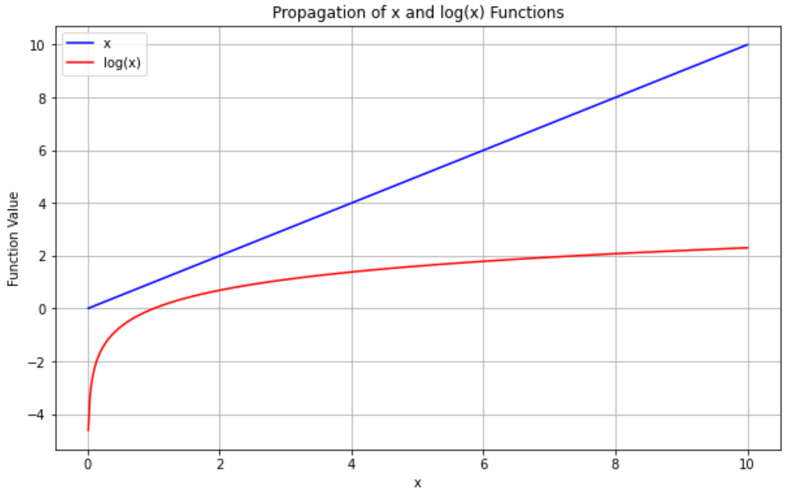

Figure 4. Examination of the propagation speeds for the mathematical expressions x and log(x)

When the graph presented in Figure 4 is analyzed, it is seen that the increase in the interval determined for the function f(log(x)) is slower than f(x). The slow increase feature enables more effective use of the representations in the negative and positive parts. It provides a manageable solution to gradient loss and gradient bursting. Furthermore, while x is defined for all real numbers, log(x) is only defined for positive values of x.

The behavior of logarithmic usage in the framework of exponential functions was also investigated. In this context, the speed of propagation between f(2^(x/log10(2))) in the Updated FELU equation and f(2^(x/ln(2))) in the original FELU activation function equation for the x0 condition is analyzed. A depiction of this situation is given in Figure 5.

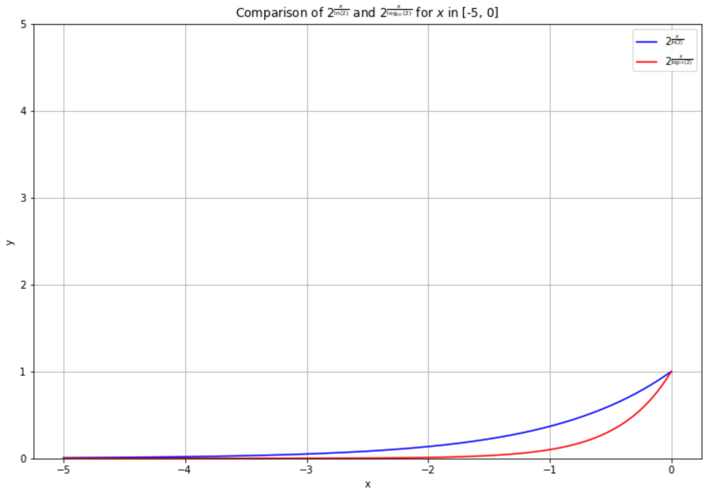

Figure 5. Examination of propagation rates for the mathematical expressions 2^(x/ln(2)) and 2^(x/log10(2))

Figure 5 shows that the propagation speed prevents an unbalanced learning process by avoiding the effect of large values. In both functions, the y-value approaches 0.

In the last stage, positive and negative value ranges were evaluated as a whole within the scope of the original and updated FELU activation function. In this context, the outputs produced for the input values are shown in Figure 6.

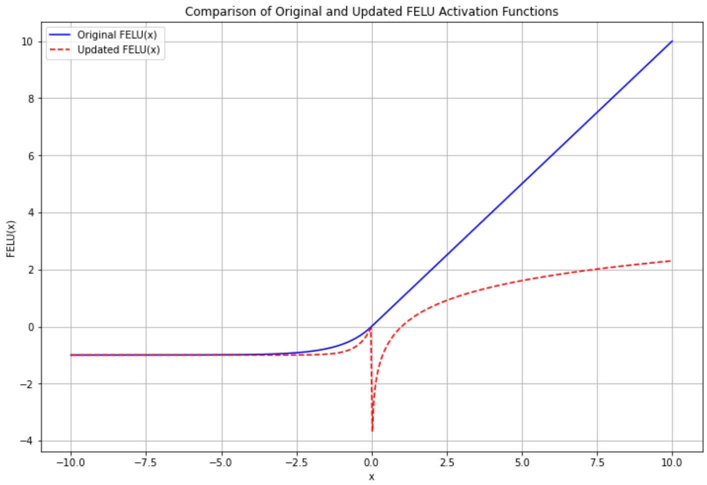

Figure 6. Examination of the propagation rates for the original and updated FELU activation functions

Figure 6 shows the propagation of the original and improved FELU activation functions. In the first step, the spread of input values over a larger period and a smaller range within the developed FELU activation function helps the neural network to learn in a more stable way by reducing the effect of large values. At the same time, this provides stability as it allows the representations to be used more effectively in the negative and positive parts. The improved FELU activation function in the second step is integrated into the sigmoid function. The developed FELU activation function has reduced the growth rate in positive regions. It must be used with caution due to its behavior only at the point x=0. The mathematical expression of the updated sigmoid function is given in equation 6.

$$\text{Updated\_Sigmoid(x)} = \frac{1}{1+e^{Updated\_FELU(x)}} \quad (6)$$

The updated sigmoid function also affects the swish function. The mathematical expression of the updated swish function is given in equation 7.

$$\text{Updated\_Swish(x)} = \text{x} * \text{Updated\_Sigmoid(x)} \quad (7)$$

Besides the updated sigmoid, swish, and FELU activation functions, the softmax activation function is not optimized.

In the third step, a hybrid activation function is proposed. The mathematical expression of the hybrid structure using Updated_Sigmoid(x), Updated_Swish(x), Updated_FELU(x), and Softmax activation functions is given in equation 8.

$$Hybrid\_Activation\_Function = Updated\_Swish(softmax(x)) \quad (8)$$

In order to produce more stable and generalizable results compared to the original activation functions, purposeful modifications were made to the activation functions. Then, a hybrid activation function is proposed to improve the model performance by combining the advantages of different functions. These optimizations have significant effects on the learning potential of the model. Because the mathematical equations of the activation functions used to interpret the outputs of the trained model relate the relationship between inputs and outputs differently. Especially on complex datasets, the construction of the most appropriate relationship provides a successful training opportunity.

RESULTS AND DISCUSSION

In recent years, deep learning has been characterized as a frequently used approach in the field of machine learning. The achievement of outputs that exceed human performance in some cognitive tasks has led to the growth of the use of the deep learning approach. One of the most important and comprehensive application areas of deep learning is healthcare (Alzubaidi et al., 2021). It is frequently preferred because it produces extraordinary performance outputs, especially within the scope of studies in the field of health (Hashimoto et al., 2020).

Deep learning makes it possible to obtain complex relationships by creating learning patterns and connections. In this structure, the output of each layer is given as input to the next layer, and a non-linear transformation is applied to the input of each layer. In this hierarchical design, the nonlinear transformation performed through activation functions is an important parameter in learning real-world problems. Therefore, the choice of activation function used to maximize success is critical. There are many research and survey studies on activation functions, which play an important role in training neural networks to learn complex representations (Wang et al., 2022; Shen et al., 2022; Apicella et al., 2021). On the other hand, nonlinear transformations performed by means of activation functions provide deeper inferences, as well as abstract and complex representations. Convolutional Neural Networks (CNNs) are specialized deep learning algorithms used to provide deep inference to classify images (Najafabadi et al., 2015).

CNNs are structures that enable pixel-by-pixel processing of images, automatically identifying the features in the image (Alzubaidi et al., 2021). However, the focus of making sense of images should not only be on classifying different images with deep learning-based architectures; the objects in each image and their locations should also be successfully predicted. These operations can lead to improved performance of neural network-based algorithms (Zhao et al., 2019). Therefore, the need for a deeper analysis of images requires that sensitive and critical points in the images to be presented as input data to deep neural network-based algorithms should be highlighted.

In medicine, image processing is actively used in many fields (Abbood et al., 2022; Yadav et al., 2024; Rawat et al., 2017; Shankar et al., 2016; Negm et al., 2018; Wang et al., 2021; Li et al., 2020). In addition, many studies have been carried out to improve detection and classification performance using image processing methods in the dental field (Khan et al., 2023; Chuo et al., 2022; Li et al., 2021; Veena Divya et al., 2017; Lin et al., 2013; Ahmad et al., 2012; Juliastuti & Epsilawati, 2012; Widodo et al., 2016; Radhiyah et al., 2016).

In this study, a CNN architecture named ToothNet is designed to classify dental images. Then, the proposed hybrid activation function is integrated into the designed CNN architecture. The updated CNN architecture is used to classify tooth images in the coronal and sagittal planes obtained from cone beam computed tomography (CBCT) scans into “No Lesion”, “Small Lesion” and “Large Lesion” categories. The classification process was managed in a hierarchical order.

In the first stage, the original images were divided into two categories: with and without lesions. Then, the proposed image processing approach was applied to the original images. The original and enhanced images, respectively, were given as input to the CNN model in which the proposed activation function was not integrated. The study was conducted using existing data. No data augmentation approach was applied. The performance metrics obtained for the fully connected layer, where the softmax activation function is used instead of the proposed activation function, are presented in Table 3.

Table 3. Performance metrics obtained with the softmax activation function in the fully connected layer for the original and enhanced images.

Activation Function	True Positive	False Negative	False Positive	True Negative	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
Original images	159	61	83	96	63.91	53.64	61.19	57.11
Processed images	139	81	43	136	68.92	76.02	62.67	68.69

Table 3 shows that when the original and enhanced images are compared, the enhanced images generally outperform the original ones. The processed images achieved improvements of 5.01%, 22.35%, 1.52%, and 11.55% in accuracy, recall, precision, and F1-score, respectively. The limitation of the study is the decrease in true positives and the increase in false negatives in the processed images. This situation represents an increase in the misclassification of truly positive examples as negative and a decrease in the proportion of correctly predicted positives. On the other hand, the true negative rate has increased, and the false positive rate has decreased. These findings indicate that the proposed image processing technique is more successful in optimizing the tooth region when there is no lesion. When all results are considered together, an overall improvement in performance is observed. This suggests that it contributes to more accurate and reliable classification in clinical applications. Therefore, in the subsequent experiments, the enhanced images were preferred.

In the second stage, softmax, sigmoid, ReLU, tanh, and the proposed hybrid activation function "proposed_aktv1" were used on images with and without lesions. The performance metrics obtained for 5 different activation functions applied in the fully connected layer are given in Table 4.

Table 4. Performance metrics of activation functions on enhanced images with and without lesions

Activation Function	True Positive	False Negative	False Positive	True Negative	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
Tanh	216	4	179	0	54.13	54.68	98.18	76.43
Sigmoid	129	91	44	135	66.17	75.42	59.73	66.75
ReLU	220	0	179	0	55.13	55.13	100	77.56
Softmax	139	81	43	136	68.92	75.97	62.67	68.68
Proposed_aktv1	169	51	69	110	69.92	61.45	68.32	64.70

When the performance metrics given in Table 4 are examined, it is observed that the "Proposed_aktv1" activation function generally achieves the most balanced and competitive results among all tested activation functions for the classification of enhanced images with and without lesions. In particular, "Proposed_aktv1" attains an accuracy of 69.92%, which is higher than the majority of the other activation functions. Its recall value of 61.45% indicates a stronger ability to correctly identify positive cases compared to activations such as Tanh and ReLU, which suffer from a high rate of false negatives. Moreover, the precision score of 68.32% demonstrates a relatively high reliability in predicting true positives while avoiding excessive false positives.

The F1-score, which harmonically balances recall and precision, reaches 64.70% for "Proposed_aktv1," ranking among the top values in the table. This suggests that the proposed activation function is more consistent in handling both sensitivity and predictive accuracy than most of the alternative activations. In contrast, activations such as ReLU, despite achieving perfect precision due to zero false positives, show extremely poor recall (55.13%), indicating that they fail to detect a large proportion of positive cases. Under normal circumstances, it is quite normal for these shared results to differ. Activation functions that add non-linearity to the architecture consist of different mathematical expressions. Therefore, they produce different outputs in different scenarios. Even a 1% increase in metrics is valuable for performance optimization. In this regard, it is observed that the recommended activation function has a higher accuracy compared to other algorithms. However, based on Table 4, it is possible to choose the softmax activation function, which gives more balanced results in a different scenario. The decision process should be determined based on the interpretation of performance metrics.

In summary, the analysis of Table 4 reveals that "Proposed_aktv1" offers a well-balanced trade-off between recall and precision, resulting in a strong F1-score and overall performance. These findings indicate that the proposed activation function can serve as a more effective and reliable approach than conventional activations for the classification of dental lesions in enhanced medical images.

In the third stage, the classification of images without lesions and with large lesions is analyzed. The dataset prepared for this scenario is tested using the proposed hierarchical scheme. The obtained evaluation metrics are given in Table 5.

Table 5. Performance metrics of activation functions on enhanced images without lesions and with large lesions

Activation Function	True Positive	False Negative	False Positive	True Negative	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
Tanh	62	46	41	138	66.67	57.43	60.22	58.79
Sigmoid	55	53	27	152	72.30	50.95	67.10	57.86
ReLU	68	40	46	133	67.57	62.96	59.65	61.25
Softmax	73	35	29	150	78.38	67.57	71.59	69.52
Proposed_aktv1	69	39	18	161	80.14	89.94	80.50	68.96

Table 5 includes the results of all compared activation functions (Tanh, Sigmoid, ReLU, Softmax, and Proposed_aktv1), allowing a clearer evaluation of their performance differences. Among them, **Proposed_aktv1** achieves the strongest and most balanced results, with 80.14% accuracy, 89.94% recall, and 80.50% precision. These metrics confirm that the proposed activation function outperforms the others overall and stands as the most effective option within this experimental setting.

Accordingly, in the fourth stage, a dataset was prepared for the scenario of classifying images of teeth without lesions and with small lesions. The evaluation criteria for the dataset tested through the proposed hierarchical scheme are given in Table 6.

Table 6. Performance metrics of activation functions for enhanced images without lesions and with small lesions

Activation Function	True Positive	False Negative	False Positive	True Negative	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
Tanh	120	59	82	30	52.67	67.03	59.41	62.00
Sigmoid	132	47	71	41	59.79	73.74	65.00	69.12
ReLU	140	39	85	27	56.85	78.21	62.22	69.32
Softmax	145	34	66	46	65.02	81.00	68.70	74.31
Proposed_aktv1	148	31	60	52	68.73	82.68	71.15	76.50

Table 6 shows the results of all activation functions (Tanh, Sigmoid, ReLU, Softmax, and Proposed_aktv1), enabling a clearer comparison of their behavior on small lesion detection. Among them, Proposed_aktv1 achieves 68.73% accuracy, with relatively high precision (62.65%) but lower recall (46.43%), indicating that the model is reliable when predicting positive cases but still misses a notable portion of small lesions. Despite this challenge, Proposed_aktv1 maintains the strongest overall balance compared to the other activation functions, confirming its superiority within this evaluation setting.

In addition, to assess whether the performance differences observed among the activation functions were statistically meaningful, a McNemar test was applied to the pairwise classification outcomes. This test, commonly used for evaluating two classifiers on the same dataset, determines whether the differences in their error distributions are statistically significant. The results of the McNemar test indicated that Proposed_aktv1 shows statistically significant improvements compared to the conventional activation functions (Tanh, Sigmoid, ReLU, and Softmax) in both large-lesion and small-lesion scenarios ($p < 0.034$). Therefore, the superior performance of the proposed activation function is not due to random variation but reflects a meaningful and reliable improvement.

The performance metrics obtained by the proposed hierarchy in the five different phases of the scenarios show a superior performance. Moreover, satisfactory outputs are provided in each scenario. This shows that the hierarchy in which the proposed activation function is integrated has a generalizable potential. Moreover, in order to compare the originality of the proposed work, we investigated the studies in the literature. Accordingly, Table 7 summarizes the purpose, method(s) used, and results obtained for similar studies in the literature using CT and CBCT datasets.

Table 7 compares the performance of various deep learning and image processing methods in the literature on lesion detection and classification in dentistry.

In (Flores et al., 2009), it was aimed to distinguish lesion types using CBCT images obtained with NewTom 3G. In this study, a 94.1% accuracy rate was achieved with Linear Discriminant Analysis and AdaBoost methods. Similarly, (Okada et al., 2015) used 28 anonymous 3D dental CBCT scans to identify dental periapical lesions and achieved an accuracy rate of 94.1% using the same methods. In (Miki et al., 2017), a dataset obtained from two dental CT units, Veraviewepocs 3D and Alphard VEGA, was used to classify tooth types in dental cone beam computed tomography (CT) images. The DCNN method used in the study achieved an accuracy rate of 88.8%. In (Wang et al., 2021), the aim was to detect oral lesions using CBCT data collected experimentally from patients. The applied CNN (Convolutional Neural Network) method achieved an accuracy rate of 98.3%. In (Esmaeilyfard et al., 2024), the aim was to diagnose and classify dental caries using an anonymized CBCT image dataset collected between January 2020 and December 2023. The applied CNN method achieved an accuracy rate of 96.2%.

In addition, (Calazans et al., 2022) studied three different scenarios on the UFPE dataset and achieved success rates between 70.00% and 81.25%. The proposed model, on the same dataset, reported success rates ranging from 68.92% to 80.14% in four different scenarios, particularly using the improved activation function. Our results, at 68.92%, 69.92%, 80.14%, and 68.73%, respectively, demonstrate generally similar performance compared to models in the literature. This suggests that model performance fluctuations may occur due to differences in the methods and data processing techniques used. Because all three studies used the UFPE dataset, the comparisons are valid and support the effectiveness of deep learning-based approaches in lesion classification.

Since improving early detection and early intervention processes is a critical parameter in dental practice, this study is planned to contribute to the literature. In the future, a new regularization method is planned to be proposed to realize a more successful, stable, and generalizable training process.

CONCLUSION

Artificial intelligence offers multidisciplinary solutions in the field of dentistry. Image processing and developed AI-based architectures are part of this solution. This is because radiographic images are shaped by the imaging process, environmental, and dynamic factors. Minimizing the negative impact of these factors using image processing approaches is valuable for image interpretation. On the other hand, producing support mechanisms for physicians with fine-tuned AI-based architectures enables the development of decision support systems. In this study, the proposed image processing approach and the fine-tuned AI-based CNN architecture were used on CBCT data, respectively. The results obtained show that optimized outputs were achieved.

Table 7. Methods used in the studies in the literature and their comparisons.

Study	Year	Data Set	Objective	Method	Accuracy (%)
(Flores et al., 2009),	2009	CBCT images from the University of Southern California Redmond Imaging Center with NewTom 3G	Differentiation of lesion types	Linear Discriminant Analysis and AdaBoost	94.1
(Okada et al., 2015)	2015	A dataset of 28 anonymized 3D dental CBCT scans	Differential diagnosis of dental periapical lesions	Linear Discriminant Analysis and AdaBoost	94.1
(Miki et al., 2017).	2017	CT dataset generated using two dental CT units, Veraviewepocs 3D and Alphard VEGA	Classify tooth types in dental cone beam computed tomography (CT) images	DCNN	88.8
(Wang et al., 2021).	2021	Data set obtained by collecting CBCT data of patients experimentally	Detection of oral lesions	CNN	98.3
(Calazans et al., 2022).	2022	UFPE public dataset (CBCT medical images)	3 different scenarios to classify tooth root lesions using dental radiographs. In scenario 1 to classify images with and without lesions in the original images. In scenario 2 to classify images with and without lesions and large lesions. In scenario 3, classify images without lesions and with small lesions.	CNN, transfer learning	70.00 in scenario 1, 81.25 in scenario 2 and 66.67 in scenario 3
(Esmaeilyfard et al., 2024).	2024	An anonymized CBCT image dataset collected between January 2020 and December 2023	Diagnose dental caries and classify the extension and location of dental caries	CNN	96.2
Proposed Models	2025	UFPE public dataset (CBCT medical images)	4 different scenarios to classify tooth root lesions using dental radiographs.	CNN, Proposed_aktv1	68.92 in scenario 1, 69.92 in scenario 2, 80.14 in scenario 3 and 68.73 in scenario 4 a

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