International Journal of Theoretical & Applied Computational Intelligence
https://ijtaci.com

Research Article

A Novel Deep Learning Approach for Classification of Abnormal Teeth in Panoramic X-rays

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Received: 6/7/2025; Revised: 17/7/2025; Accepted: 18/7/2025; Published: 29/7/2025

https://doi.org/10.65278/IJTACI.2025.7

Abstract: Dental professionals can identify common dental conditions including caries with the use of panoramic and periapical radiograph techniques. In most cases, panoramic and periapical pictures are used by dentists to physically diagnose problematic teeth. Unnoticeable aberrant teeth can result via manual diagnosis for a number of reasons, including inexperience and carelessness brought on by a tremendous workload. Therefore, in order to avoid these drawbacks, advanced computer vision technologies along with Data-driven image enhancement techniques are required. Convolutional Neural Networks (CNNs) are recognized for their ability to utilize multiple convolutional layers, resulting in superior classification accuracy. Consequently, they represent one of the most effective methodologies for diagnosing dental abnormalities. However, the classification process using CNNs necessitates a substantial dataset of images to ensure adequate training and to achieve satisfactory performance outcomes. This study proposes a modified output layer for the ResNet-50, MobileNet V2, and Lightweight Convolutional Neural Networks (LWCNN) models to classify panoramic and periapical images into four distinct categories: quadrant, quadrant-enumeration, quadrant-enumeration-disease, and unlabeled. The unsharp filter, histogram equal, and complement image were among the methods applied to the chosen image samples in order to create a different perspective on the dataset. Training and testing accuracy for ResNet-50, MobileNet V2, and LWCNN were 38.56, 62.13, 63.91, 34.06, 22.83, and 26.38, respectively. On the other hand, the CNN models in the second scenario obtained training and testing accuracy of 99.80%, 99.60%, 99.90%, 93.20%, 96.50%, and 96.60% respectively. This outcome demonstrates that the suggested LWCNN model can successfully aid in the classification of abnormal teeth.

Keywords: Deep Learning; Light Weight Convolutional Neural Networks; ResNet-50; MobileNet V2; Classification.

1. Introduction

Dentistry defines Abnormal teeth (At) as an outcome of a complicated interaction between the fermentable carbohydrates and the dental clanged bacteria that produce acids. Children, teenagers, and elderly people are more prone to this popular illness. Their dentine and enamel can be affected by acids in the dental plaque, thereby demineralization happens causing one of the initial symptoms - white spot lesions. When it persists, little holes emerge which are so-called caries. However, early care of teeth prevents serious damage to tooth layers and, therefore, prevents severe toothache, infection, and tooth loss [1,2,3].

Periapical radiographs provide detailed images of teeth and surrounding tissues, which help diagnose dental issues like abnormal teeth, gum disease, and bone loss by showing the teeth, roots, and alveolar bone. This imaging method is crucial in dental radiology for obtaining complete views that assist in diagnosing various dental conditions, including impacted teeth and broken fragments. However, caries detection using these imaging techniques is typically done manually by dentists, which can lead to errors due to inexperience or high patient volume, potentially allowing caries and severe dental problems to go unnoticed. To address these challenges, machine learning and image processing-based automatic systems have gained importance, aiding in detecting dental issues such as periodontitis and cysts, although research on these technologies for dental diagnostics remains limited.

In most of these studies, traditional machine learning-based feature extraction methods were used to detect dental diseases [4,5,6]. In other studies, [7,8] segmentation and classification processes were performed using deep learning models. Besides, few studies are based on deep CNN architectures on dental X-ray images. Also, applications for abnormal teeth detection using deep CNN architectures are even more limited in quantity and inadequate in this area [9,10]. In the majority of these studies, traditional machine learning-based feature extraction methods have been employed for the detection of dental diseases [5,6]. Conversely, other research efforts [7,8] have utilized deep learning models for segmentation and classification processes. Furthermore, there is a scarcity of studies that focus on the application of deep Convolutional Neural Network (CNN) architectures to dental X-ray images. The use of deep CNN architectures for the detection of dental abnormalities remains particularly limited and insufficiently explored in the existing literature [11,12].

In experimental studies, 2,536 periapical images, including a modified output layer to classify panoramic and periapical images into four groups: quadrant, quadrant-enumeration, quadrant-enumeration-disease, and unlabeled. These results have revealed that the proposed model for classifying panoramic and periapical images will significantly contribute to dentists' performances. Based on the LWCNN ensemble. The major contributions of the proposed model are:

- The sharpening filter and intensity colourmap procedures used in this study further highlight the decayed area in the unprocessed dental images.
- Although there are studies on abnormal teeth in the literature, there is no publicly available data set. In this paper, a new dataset consisting of 2,536 images (quadrant, quadrant-enumeration, quadrant-enumeration-disease, and unlabeled) was presented, and this dataset was made freely accessible to researchers.
- Pre-trained ResNet-50, Mobile Net V2, and LWCNN architecture based on the transfer learning approach in abnormal teeth classification techniques were adopted.

2. Literature Review

The lack of aberrant teeth identification studies in the literature is obvious, and their existence is limited to applying periapical and panoramic imaging methods. Our study acroases these limitations and exploits conventional feature extraction techniques that are frequently combined with pre-trained deep models. A rapid revision of the most associated studies will be conducted.

A multi-step framework was developed that includes dental instance detection, healthy instance filtering, and abnormal instance classification, achieving an F1 score of 0.76 for the multi-label classification of dental diseases [9]. Another study utilized a unified method with CNNs for detecting teeth and segmenting cavities, achieving over 90% precision and recall [10]. The fusion of handcrafted features with deep learning architectures has been shown to enhance the detection of specific dental structures, such as maxillary incisors and canines, improving diagnostic capabilities by approximately 1.7% [11]. The YOLO-v6 demonstrated a mean average precision of 70.76% in detecting various dental diseases, showcasing the potential of real-time object detection in clinical settings [12]. Geetha et al. employed back-propagation neural networks, window-based adaptive thresholds, and Laplacian filtering techniques to process dental X-ray images. The back-propagation neural network utilized several statistical feature extraction methods to classify the newly acquired images, achieving a success rate of 97.1% in the identification of caries using a dataset of 105 periapical dental X-ray images [6]. Additionally, Prajapati et al. applied a transfer learning approach utilizing the pre-trained VGG16 model to analyze 251 periapical dental X-rays. In the investigation conducted for three different classes, the fully trained network architecture produced carries images with an 88.46% performance [13].

The automated caries detection system developed by Singh and Sehgal [14] was based on Radon Transformation (RT) and Discrete Cosine Transformation (DCT). The Principal Component Analysis (PCA) method was employed for feature extraction. When applied to the Random Forest classifier, the model achieved an accuracy of 86%. In a separate study, Casalegno et al. [15] proposed a method for identifying dental cavities in images obtained through near-infrared transillumination (TI) imaging technology. Their convolutional neural network design yielded receiver operating characteristic (ROC) areas of 83.6% for occlusal lesions and 85.6% for proximal lesions. Additionally, Cantu et al. [7] conducted a study focused on the identification of caries lesions in 3,686 bitewing radiographs. The U-Net convolutional neural network architecture was applied to teeth exhibiting anomalies, resulting in an accuracy of 80% for the proposed model.

A hybrid strategy comprising steps of segmentation, classification, and decision-making was proposed by Tuan et al.,[16]. The segmentation technique is based on fuzzy clustering that is semi-supervised. A new graphic-based clustering technique was also used for categorization. The suggested performance of the approach has been shown to be 90% for five different carry classes. 1700 panoramic dental X-rays were used in a study by Lakshimi and Chitra to identify cavities. The deep CNN architecture and conventional segmentation methods were compared with the performance outcomes. With the graph cut and deep CNN approach, a 98.6% success rate was attained [17]. Increasing the accuracy of panoramic dental X-ray pictures and making it easier for specialists to identify remedies were the goals of the study conducted by Naam et al. A variety of morphology gradient algorithms have been created in addition to popular methods for image processing include cropping, morphology erosion, and morphology dilation. By improving the clarity of the dental X-ray image, the enhanced pre-treatment phase made it easier to detect caries [18]. A method was presented by Oprea et al. [19] to classify the kind of caries seen in dental radiography after assessing the size of the existing caries lesion. In the x-ray, the edge detection approach was used to segment the dentition. Subsequently, they determined the amount of caries pixels (black areas) that damaged the teeth and categorized them based on size.

In order to compare caries detection, Obuchowicz et al. [5] used certain texture feature mapping techniques. Histogram Stretching (HSTR) was used to pre-process the original pictures. When the textural feature map approaches were compared, it was found that the energy parameter offered the most valuable information. Furthermore, the entropy parameter was said to have done a good job of visualizing the caries-affected areas. For the purpose of identifying aberrant teeth from periapical dental X-ray pictures, Lee et al.,[20] employed the Google Net Inception v3 CNN architecture. A periapical data collection of 3000 pictures was employed in the proposed study for 2400 training and 600 testing. According to the findings, the premolar, molar, and combined premolar and molar caries models had respective success rates of 89%, 88%, and 82%. The goal of Naam et al. [21] was to enhance X-ray picture quality for identifying proximal caries specialists. They produced a collection of dental X-ray pictures that included 27 proximal problematic teeth. Clear images of the object edges have been produced using the suggested Multiple Morphological Gradients approach. The findings imply that the model can be applied to accurately characterize stages of progression and proximal caries. A hybrid model combining Deep Neural Network and Artificial Neural Network approaches was presented by Leo and Reddy [22]. They used 180 testing and 300 training dental x-ray images in their experimental investigations. For the classification of aberrant teeth, the suggested method produced a 96% success rate.

A system based on deep learning and morphological techniques was created by Majanga and Viriri [23]. During the preprocessing phase, thresholding techniques with Gaussian blur filters were used to identify the borders of tooth images. Later, features derived from deep learning were used to classify dental images as either caries or non-caries based on a predetermined threshold value. Based on periapical dental X-ray scans, they employed data augmentation techniques to acquire 11,114 tooth pictures. This led to a 97% success rate for the suggested caries detection model Vinayahalingam et al. [24] conducted a study based on the assessment of deep learning architectures' classification performance using panoramic X-ray pictures. To train CNN architecture, 400 cropped panoramic x-ray images were employed. In experimental studies, it was observed that they achieved 87% performance with the Mobile Net V2 architecture.

The further paper is organized into three main sections, section 3 presents materials & methodology, section 4 presents experimental results & their analysis. Finally, section 5 concludes research.

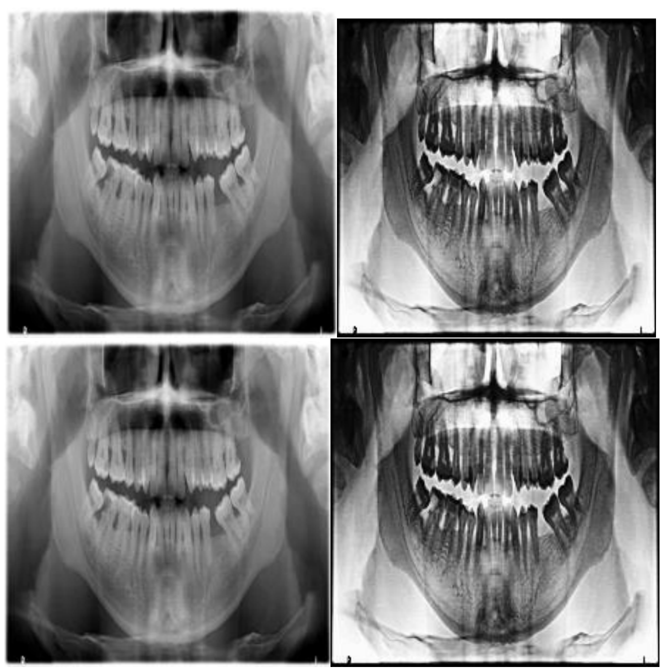
3. Materials and Methods

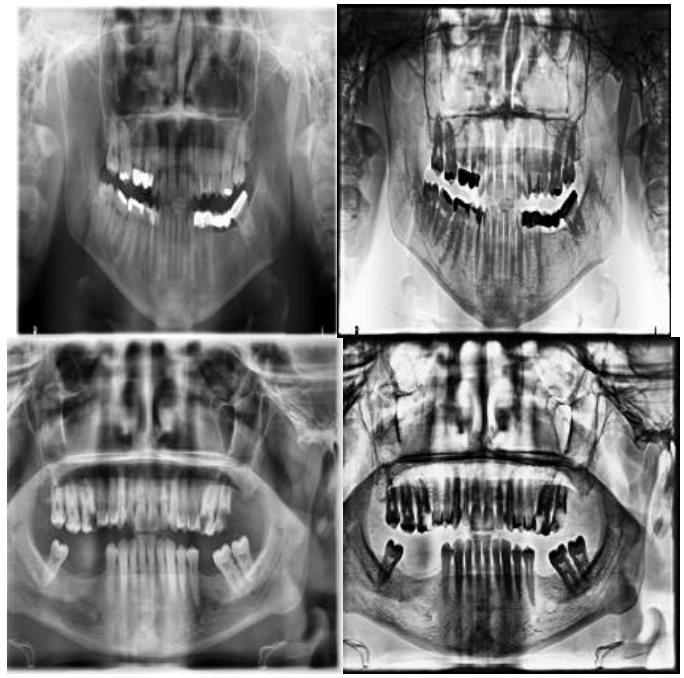
3.1. Methods

This section presents the suggested framework for classifying the DENTEX [25,26] dataset, which consists of panoramic dental x-rays taken from three distinct institutions under standard clinical settings but with different imaging protocols and equipment. The varied image quality reflects disparate clinical practices. To ensure the protection of patient privacy and confidentiality, the dataset utilized in this study comprises periapical and panoramic images of patients aged 12 years and older, randomly selected from the hospital's database. The proposed convolutional neural network (CNN)-based X-ray image classifiers were implemented and executed using Python 3 on a Windows 10 computer equipped with an AMD Ryzen 53550H CPU, operating at 2.10 GHz with Radeon Vega Mobile GFX, and 16 GB of DDR4 RAM. We also provide sufficient information to overcome the drawbacks of databases for high resolution and feature extraction. We employ two pre-trained models, such as LWCNN, ResNet-50, and MobileNet V2, for this purpose. The actual datasets used in all three tests are from the initial 224×224×3 size that was intended to be carried out using the proposed CNN model.

3.2. Balanced Dataset

We observed a significant disparity in the number of images that make up the four classes (quadrant, quadrant-enumeration, quadrant-enumeration-disease and unlabeled) in the data set as shown in Fig 1. Since the dataset contains different numbers of images for each category, the images must all be equal to prevent bias for the class with more images than the other and to get more accurate findings. Due to the aforementioned factors, we advise deleting some of the subpar imagegraphs in order to depend on the DENTEX images as little as possible. The total amount of datasets is 2,536, and there will be 634 images for each category in the final stage. During the system phases, the dataset was divided into 80% for training and testing and 20% of the WSI image dataset was used for system testing (80:20), 507 images for training, and 127 for system testing.





(a) (b)

Figure 1: Sample Datasets (a) Before and (b) After Preprocessing.

3.3. Balanced Dataset

In this model, we employed five hidden layers [27]. Batch Normalization, Leaky Relu, and Max Pooling layers are included in each layer to address weight scattering and extract significant features from the images. The CNN with these layer components is depicted in Figure 2, and Table 1 below provides more information about it.

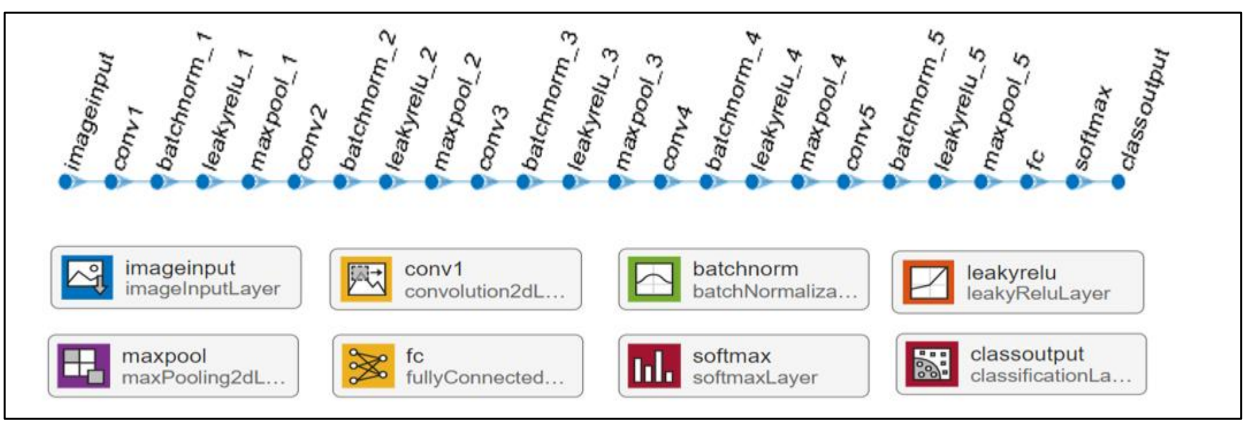


Figure 2: LWCNN Architecture

Table 1: Architecture of the proposed LWCNN model

Name of layer	Decimation	# of Filter	Padding	Stride
Input	224x224x3			
Conv1	3x3	8	Same	
Bath normalization				
Leaky Relu	0.01	1		
Max pooling	2x2			2
Conv2	3x3	16	Same	
Bath normalization				
Leaky Relu	0.01			
Max pooling	2x2			2
Conv3	3x3	32	Same	
Bath normalization				
Leaky Relu	0.01			
Max pooling	2x2			2
Conv4	3x3	16	Same	
Bath normalization				
Leaky Relu	0.01			
Max pooling	2x2			2
Conv5	3x3	8	Same	
Bath normalization				
Leaky Relu	0.01			
Max pooling	2x2			2
Fully connected		4		
Softmax Classification		0 or 1 or 2 or 3		

3.4. Analysis of DENTEX Images

In this study, we have two scenarios: In the first scenario, we reduced all dataset images to 224, 224, 3 from their original size in order to accommodate the LWCNN, ResNet-50, and MobileNet V2 models, as illustrated in Figure 3. Furthermore, we have a variety of image sizes at our disposal. To get around these issues, all of the imagegraphs must be the same size in order to produce more realistic results.

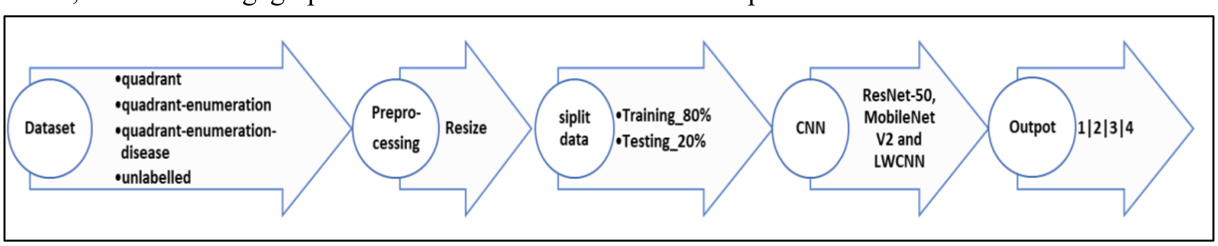


Figure 3: Scenario (1) training on the three models with original datasets.

In the second scenario, as illustrated in Figure 4, we created a new presentation of the dataset [25,26] using the same previous images that had been improved using a range of image-editing techniques, including the Unsharp filter, Histogram equal, and Complement image. This gives the images more depth. The methods for altering images are:

3.4.1. Unsharp filter

The unsharp filter is a basic sharpening tool that enhances edges (and other high-frequency components in a picture) by subtracting an unsharp or smoothed version of the original image. In the printing and imagegraphic industries, the unsharp filtering process is frequently employed to produce sharper edges. Using Equation 1, unsharp masking creates an edge image g (x, y) from an input picture f (x, y).

$$(x, y) = f(x, y) - fsmooth(x, y) \quad (1)$$

3.4.2. Histogram equal [27]

The second process used to adjust the intensities of DENTEX images to enhance contrast is depicted in Fig. 3. The overall contrast of several images is frequently improved by this method when an image is represented by a limited range of intensity values. The method can improve detail in images that are either over- or under-exposed, as well as the success of bone structure in DENTEX images. Using the entire spectrum of intensities, this modification allows the intensities on the histogram to be more evenly distributed. As a result, areas with fewer local contrasts can gain greater contrasts. Histogram equalization is used to accomplish this, efficiently distributing the densely packed intensity values that once diminished visual contrast.

3.4.3. Complement image

The complement image is the last stage in this study's DENTEX picture enhancing process. This method turns zeros into ones and ones into zeros by flipping the pixels with zero and one hues [28]. In other words, each pixel count in the grayscale or color image's equivalent is deducted from the maximum pixel value permitted by the category (or 1.0 for double-precision images). The difference also serves as the value of a pixel in the final image. In the final image, darker portions become lighter and brighter areas become darker. In color pictures, reds turn cyan, greens turn magenta, blues turn yellow, and so on. Additionally, when these updated images were trained as shown in Fig. 4, outcomes rose much more, and we can say that these findings are superior to those of the initial test.

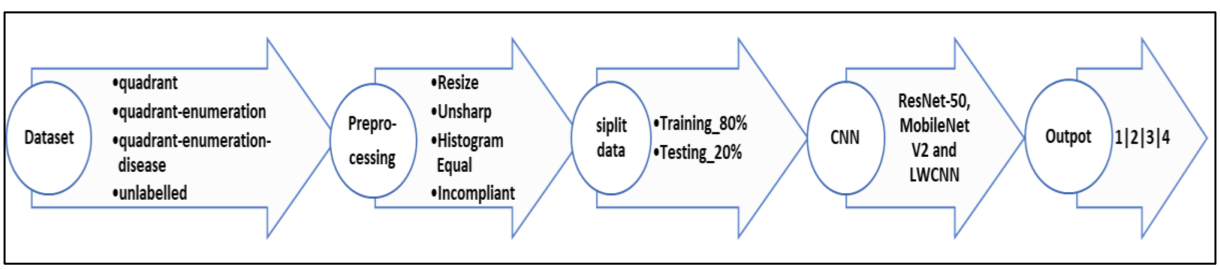


Figure 4: Scenario (2)- training on the three models with enhanced datasets.

3.5. Training Stage

The training stage of the data samples is accomplished using Python3. The steps that make up training data are as follows:

1- Defining libraries: Defining the necessary libraries that are needed in the training, extracting features, classifying and the testing process, and then extracting the results, the most important libraries are (Keras and TensorFlow)
2- Recall the images: “ImageDataGenerator” is used to carry and manage the images from Google Drive.
3- Checking the data: “Name_file.flow_from_directory” is employed to check and compile the number of pictures in each category (classes).
4- Create the network model: It involves Input, hidden and output layers.

4. Experimental Results

The training outcomes of LWCNN and ResNet-50 MobileNet V2 are covered in this section. As seen in Figs. 5, 6, and 7, these CNN models apply 20 epochs, meaning that every kind of dataset is processed 20 times during the training phase. Table 2 displays the performance details of the outcomes for scenarios (1) and (2).

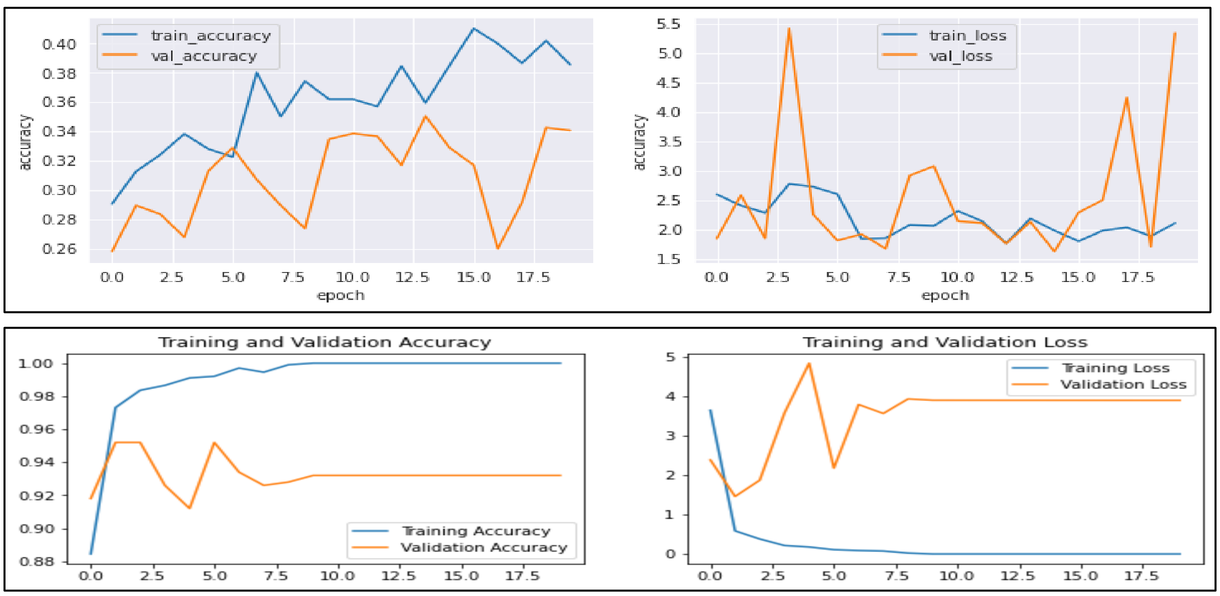


Figure 5: Accuracy and Loss of training dataset with (ResNet50 model) in S1 and S2.

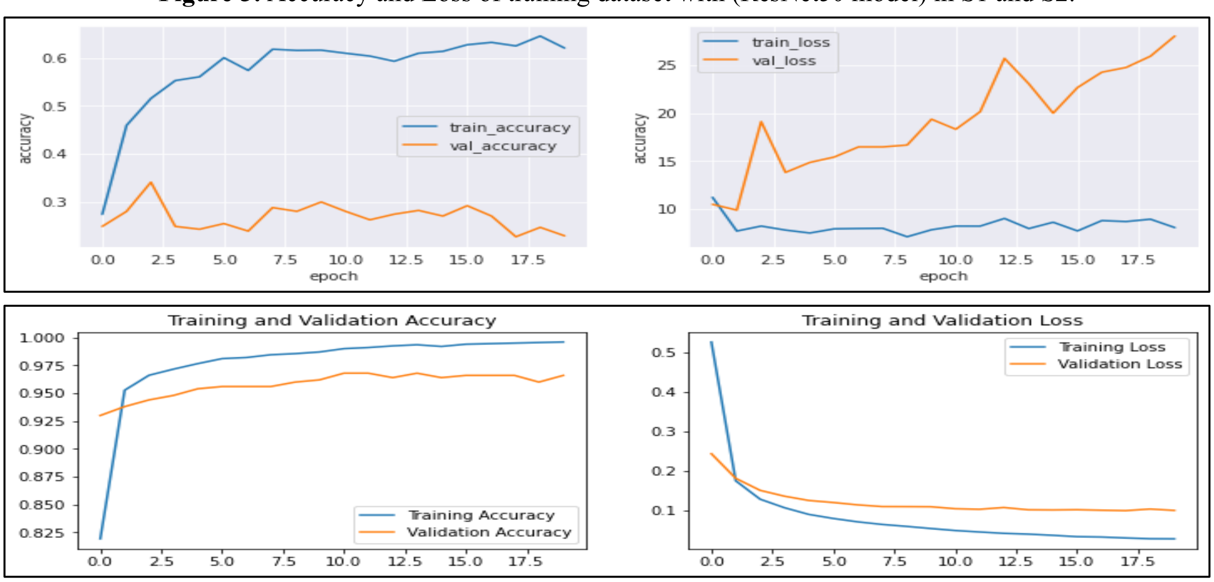


Figure 6: Accuracy and Loss of training dataset with (MobilNetV2model) in S1 and S2.

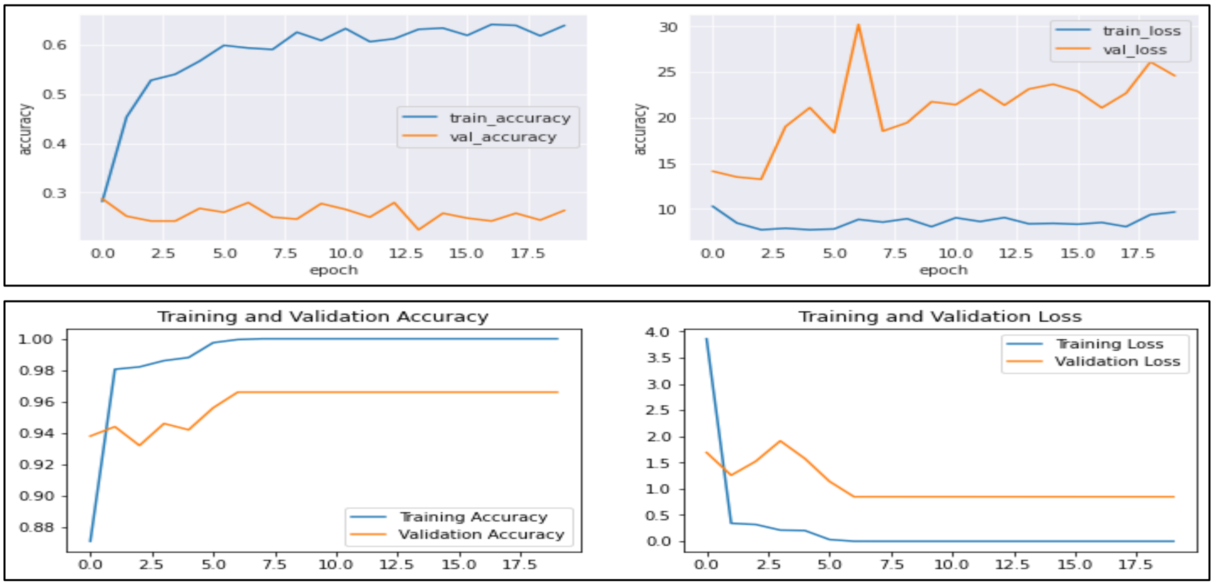


Figure 7: Accuracy and Loss of training dataset with (LWCNN model) in S1 and S2.

The performance measures used in this study are the most widely used metrics shown below in equations .1 are training and testing accuracy in [29] which are given as:

$$\text{Accuracy} = \frac{TN + TP}{TP + FP + TN + FN} \tag{1}$$

Table 2: Comparison between the results of the Scenario-1(S1) and Scenario-2 (S2).

Model	(S1) AC-Tr.	(S2) AC-Tr.	(S1) AC-Te.	(S2) AC-Te.
ResNet50	38.56	99.80	34.06	93.20
MobilNetV2	62.13	99.60	22.83	96.50
LWCNN	63.91	99.90	26.38	96.60

In the comparative analysis presented in table 2, we can observe nuanced differences in the performance of the three deep learning models, ResNet50, MobilNetV2, and the LWCNN Proposal, across the two experimental scenarios, S1 and S2. In the first scenario (S1), where the input images were resized to a standardized 224x224x3 dimension, LWCNN model demonstrated the highest training accuracy at 63.91%, outperforming both the ResNet50 and MobilNetV2 models. However, in the testing phase, the LWCNN model's accuracy decreased to 26.38%, while the ResNet50 and MobilNetV2 models achieved 34.06% and 22.83%, respectively. Conversely, in the second scenario (S2), where the input images were enhanced using various image processing techniques, all three models exhibited 99.90% training accuracy, suggesting the efficacy of the data augmentation approach. During the testing phase, the LWCNN and MobilNetV2 models maintained a high level of performance, achieving 96.60% and 96.50% accuracy, respectively. Interestingly, the ResNet50 model demonstrated a substantial improvement in testing accuracy, reaching 93.20% compared to its S1 performance.

These results highlight the importance of carefully selecting and optimizing the preprocessing techniques employed in deep learning tasks, as they can significantly impact the models' generalization capabilities. The contrasting outcomes between the two scenarios underscore the need for comprehensive evaluation and thoughtful model selection to address the unique challenges present in the problem domain.

5. Discussion

Table 3 offers a comprehensive overview of the various deep learning-based approaches employed for the analysis of chest X-ray images across multiple studies published from 2020 to 2024. The comparative analysis showcases the diverse methodologies, network architectures, and input dimensions utilized by researchers in this domain. We can observe the progression of techniques from the initial use of simpler models, such as k-means and CNN, to the subsequent adoption of more sophisticated architectures, including U-Net, Net-B5, GLCM, and AlexNet. The number of X-ray images input also exhibits a significant increase, from as low as 105 in early studies to as high as 11,114 in the more recent work. Notably, the training accuracy of the models has steadily improved over time, with the most recent proposed approach, which combines ResNet-50, MobileNetV2, and LWCNN, achieving an impressive 99.90% accuracy. This advancement highlights the continuous efforts of the research community to enhance the performance and robustness of deep learning-based solutions for chest X-ray analysis, a crucial task in the field of medical imaging and disease diagnosis.

Table 3: Comparison between related works.

Reference / Year	Method	Number of x-rays	Dim	Training Accuracy (%)
[4] / 2020	k-mean	-	Non	92.00
[6] /2020	CNN	105	Non	97.10
[7] / 2020	CNN, U-Net, Net-B5	3,686	512x416	80.00
[19] / 2020	CNN, GLCM, and AlexNet	1700	Non	98.60
[24] / 2021	HNN and CNN	480	Non	96.00
[25] / 2021	CNN	11114	Non	97.00
[26] / 2021	CNN and MobileNet V2	500	256x256	86.00
[9] / 2023	Faster-RCNN, U-net and Vgg16	-	80x80	76.00
[10] / 2023	CNN	968	Non	95.40
[12] / 2023	CNN	664	416x416	70.76
[11] / 2024	CNN	-	2x2 and 3x3	98.70
	ResNet-50			99.80
Proposed	MobileNet V2 and			99.60
model	LWCNN			**99.90**

6. Conclusion

In the examination of images of aberrant teeth, deep convolutional neural networks (CNNs) are commonly used. This study used two CNN models (Resnet50 and MobileNet-v2) with a reduced output layer from 1000 to 4 classes for scenario (S1) and experiment (S2), respectively, and created a new model dubbed the lightweight convolution neural network (LWCNN) model. As a preprocessing step, image enhancement techniques increase classification accuracy. The outcomes were validated by comparing two trials without any dataset augmentation. As a preprocessing step, image enhancement techniques increase classification accuracy. Only the original dataset was used to test the models in the first scenario. The accuracy scores for training and testing were 38.56, 62.13, 63.91, 34.06, 22.83, and 26.38, respectively. In the latter case, improved datasets have been used to test the model to increase its reliability. Its accurate scores for training and testing were 99.80, 99.60, 99.90, 93.20, 96.50, and 96.60, respectively. Based on the experimental findings, this study concludes that the preprocessing of the dataset improved the classification output. Developing more efficient techniques and incorporating several World Health Organization-approved datasets may be part of future research. To help medical practitioners identify abnormal teeth early, a comprehensive system might be built to speed up data analysis.

Funding: No specific funding received for this research.

Data Availability: The data that support the findings of this study are openly available in (GitHub) https://github.com/ibrahimethemhamamci/HierarchicalDet

Conflicts of Interest: No conflict of interest is stated by the author

Authors contributions. Conceptualization: HFM, HAML, AS; methodology: HFM, HAML, BNAA, MSA, AS, validation: MSA, AS; writing—original draft preparation: HFM, HAML, BNAA, MSA, AS; writing—review and editing: HFM, HAML, BNAA, MSA, AS; visualization: HFM, AS; supervision: MSA, AS; project administration: HFM, HAML; The author had approved the final version.

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