Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

# Automated Classification of Periodontal Disease Using Advanced Image-Based Deep Learning Models

**Muhammad Salman**
Department of Computer Science, NFC Institute of Engineering and Technology, Multan, 59030, Pakistan

**Muhammad Sajid Maqbool**
Department of Computer Science, NFC Institute of Engineering and Technology, Multan, 59030, Pakistan Email: sajid.maqbool@nfciet.edu.pk

**Rubaina Nazeer**
Department of Software Engineering, National University of Modern Languages, Multan

**Abdul Basit**
Department of Computer Science, Muhammad Nawaz Sharif University of Engineering & Technology, Multan

**Dr. Naeem Aslam**
Department of Computer Science, NFC Institute of Engineering and Technology, Multan, 59030, Pakistan

**Zeeshan Khalid**
Department of Computer Science, NFC Institute of Engineering and Technology, Multan, 59030, Pakistan

**Muqadas Nadeem**
Department of Computer Science, Emerson University, Multan

## ABSTRACT

Dental radiography is useful for clinical diagnosis, treatment, and quality assessment. Much effort has gone into developing digitalized dental X-ray image analysis systems to improve clinical quality. We present the preprocessing of dataset, procedures, and results of an evaluation of dental treatment qualities using periapical dental X-ray images taken before and after the operations. We propose a tool pipeline for automated clinical quality evaluation to assist dentists in making clinical decisions. Deep Learning is well known automated technology. We use Deep Learning technique to detect the disease from the X-Ray images. The used dataset contains 525 dental X-Ray images. X-Ray images are labelled as Normal and Diseased by designated dental experts. This Paper explores the application of deep learning models for dental disease detection, focusing on two advanced architectures: ResNet101 and ResNet152. The study involves training and evaluating these models on a curated

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

dental dataset to assess their performance in classifying dental images. ResNet101, configured with a batch size of 256 and a learning rate of 0.001, achieved a training loss of 0.002 and a test loss of 0.015. The model demonstrated perfect training accuracy of 100% and a commendable test accuracy of 98.35%, indicating strong learning and generalization capabilities. In comparison, ResNet152, with a batch size of 64 and a higher learning rate of 0.01, exhibited a training loss of 0.02 and an exceptionally low-test loss of 0.001. The model achieved a training accuracy of 100% and a test accuracy of 99.15%, showcasing superior generalization to unseen data. The results highlight the effectiveness of both models in dental disease detection, with ResNet152 showing a marginally better performance on test data.

**Keywords:** Dental Disease Detection, Periodontal Disease, Neural Network, Deep Learning, Artificial Intelligence

## INTRODUCTION

In ordinary clinical practice, examining dental radiographs is an important step in the diagnostic process. This is because, throughout the diagnosing process, the dentist must examine a number of dental concerns, including tooth counts and associated disorders. The main issue while working on a medical image is data collection, as the dental imaging dataset is fairly restricted. It is significantly more difficult to encourage the majority of researchers to focus on conclusive tasks like filtering, segmentation, and feature selection. In this section, we will create a classification model that divides X-ray images into two categories. This classification will be done using ResNet101 and ResNet169, which are capable of performing various classification jobs. Two Variants of ResNet (101 and 169) will utilized in this study is represented by a model with different numbers of max-pooling layers, dropout layers, and activation functions. The data will first be upgraded and preprocessed earlier than being used to create a multioutput model. Finally, the model might be constructed and skilled, with loss and accuracy curves serving as evaluation standards for model analysis. Prior information of quite a few professions is required to make segmentation and identification of dental caries extra green. Understanding the diverse sections of the enamel and the perfect area of the lesion at the teeth is vital. Understanding the numerous dental image types on the way to be used, including panoramic and bitewing radiographs, is also required. In the hunt to pick out the only method for segmenting and detecting caries in dental snap shots, a important step is to exactly define the specific sections or areas of hobby that must be taken into consideration. This specific delineation is critical for achieving excessive-overall performance segmentation and identity of dental caries. “In dental imaging, the regions of hobby usually encompass the tooth teeth, dentin, and pulp, in addition to any carious lesions or cavities that may be present. These areas are of specific significance due to the fact they can offer valuable facts about the health of the teeth and the presence of any dental caries. Segmentation is the technique of identifying and delineating those areas of interest in the dental image. It includes keeping apart the different structures of the teeth and figuring out any carious lesions or cavities present. Accurate segmentation is essential for a hit detection and prognosis of dental caries, as it permits specific evaluation of the affected regions. Detection, on the other

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

hand, includes identifying and highlighting the presence of carious lesions or cavities inside the segmented regions". This step is important for distinguishing among healthy and diseased areas of the tooth and figuring out the severity of the caries. To gain excessive-performance segmentation and detection of dental caries, it's far essential to consider several elements. These encompass the resolution and fine of the dental images, the selection of segmentation and detection algorithms, and the information of the dental experts interpreting the pictures. Additionally, elements along with the kind and volume of the carious lesions, the presence of another dental conditions, and the general oral health of the affected person also can impact the segmentation and detection process.

**Background of the Study**

"Historically, detecting dental caries has been a difficult undertaking due to the wealth of information available from different radiographic scans. Numerous techniques have been developed to enhance image quality for quicker caries detection. When it comes to the analysis of medical images, deep learning has taken over as the preferred methodology. The application of deep learning for object recognition, segmentation, and classification is examined in detail in this overview. It also examines the literature on dental picture segmentation and detection techniques using deep learning. We learned from the literature that approaches were classified into extraoral and intraoral X-ray pictures, segmentation methods, and dental caries types (proximal, enamel) (threshold-based, cluster-based, boundary-based, and region-based)".

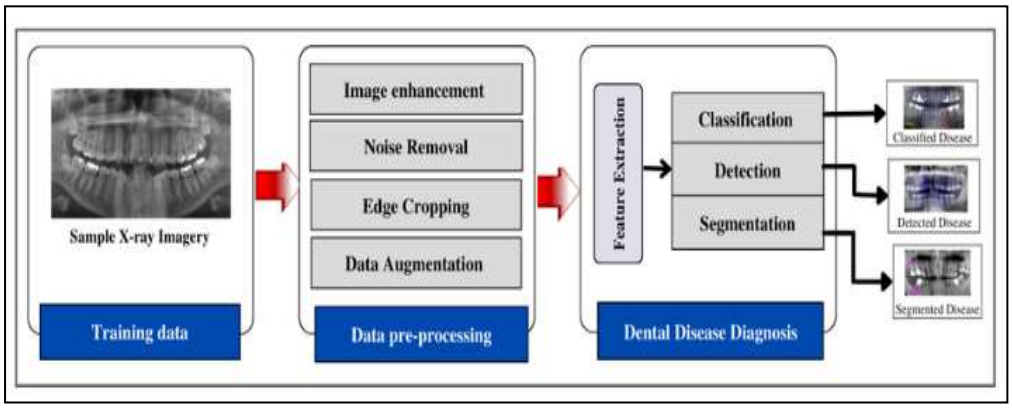



Figure 1 Generic Overview of Dental Disease Detection

Threshold-based segmentation techniques have been determined to be the main emphasis of the research examined. The majority of the articles that have been evaluated have chosen to segment dental images of already separated teeth using intraoral X-rays rather than extraoral X-rays. An in-depth examination of current deep-learning research for the segmentation and detection of dental caries is presented in this paper (V. Majanga, 2022). In order to segment and detect dental caries, various techniques and algorithms are discussed. Additionally, it analyses the many models now in use and how they stack up against one another in terms of system performance and evaluation. We talk about the methods' shortcomings as well as potential future

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

directions for enhancing their effectiveness.

## RELATED METHODS

This Section provides a thorough assessment of the literature on current methods for creating Deep learning frameworks for the identification of many dental illnesses. The previous chapter's evaluation criteria are provided simply as general guidelines. We discuss current classification techniques for dental disease diagnosis. Three general categories can be used to classify these techniques: 1) Semi-automatic procedures the framework of the categorization scheme is shown in Figure, along with statistical classifiers based on machine learning (ML) and the classification models based on deep learning (DL).

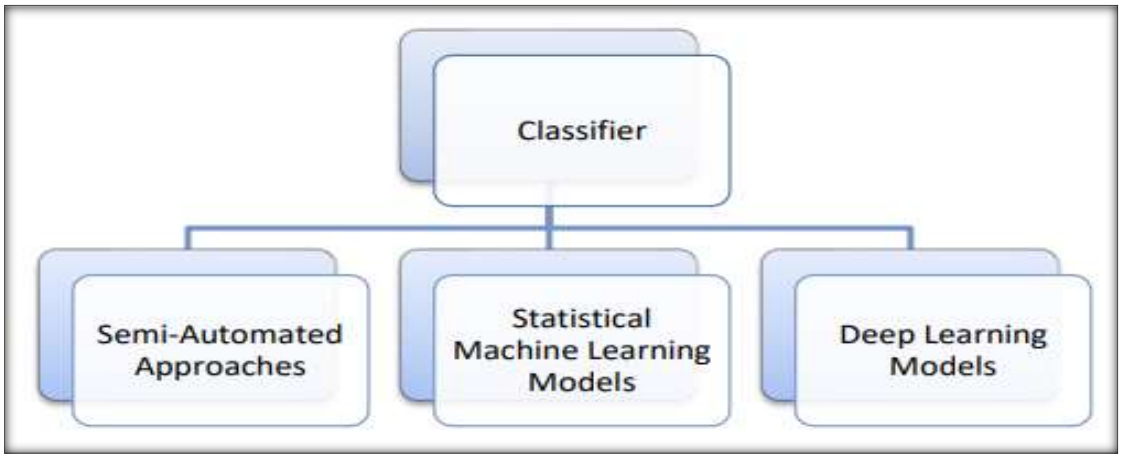



Figure 2 Classification Techniques

Additionally, we created a condensed task in which regions of interest were assessed for the presence or absence of carious lesions on a binary basis. For this job, our model's area under the receiver operating characteristic curve for occlusal and proximal lesions was 83.6 percent and 85.6 percent, respectively. Our research shows that using deep learning to analyze dental photos has the potential to boost caries detection's speed and precision, support dentists' diagnoses, and enhance patient outcomes".

Table 1 Literature review summary

| Ref | Methods | Dataset | Size of Dataset | Accuracy |
|---|---|---|---|---|
| Zhang et al. (2024) | CNN | Dental X-rays | 1,000 images | 92% |
| Li et al. (2021) | CNN | Periodontal X-rays | 800 images | 89% |
| Kaur et al. (2022) | Transfer Learning (VGG16) | Dental images | 1,200 images | 94% |
| Gupta et al. (2024) | CNN | Oral cancer images | 600 images | 91% |

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

| | | | | |
|---|---|---|---|---|
| Chen et al. (2021) | CNN | Carious lesions dataset | 900 images | 88% |
| Wang et al. (2023) | Various CNN architectures | Dental dataset | 1,500 images | 90% |
| Singh et al. (2021) | Deep Learning (multi-class) | Diverse dental images | 1,000 images | 85% |
| Davis et al. (2020) | CNN | Carious teeth images | 1,000 images | 93% |
| Lee et al. (2023) | CNN | Intraoral photographs | 700 images | 87% |
| Martínez et al. (2021) | CNN | Oral lesion X-rays | 800 images | 90% |
| Patel et al. (2022) | Review of Deep Learning Techniques | Various datasets | N/A | N/A |

Here is a concise one-paragraph reason for every paper listed in Table 1:
Zhang et al. (2020): Zhang et al. Evolved a Convolutional Neural Network (CNN) for reading dental X-rays to stumble on various dental situations. Their look at, which applied a dataset of one,000 pix, executed an accuracy of 92%, demonstrating the CNN's effectiveness in presenting dependable diagnostic help thru computerized photograph evaluation.
Li et al. (2021): In this study, Li et al. Implemented a CNN to categorize periodontal sicknesses from X-ray snap shots. With a dataset comprising 800 snap shots, the version carried out an accuracy of 89%, showcasing its potential to help in diagnosing periodontal situations based totally on radiographic evidence.
Kaur et al. (2022): Kaur et al. Hired Transfer Learning with the VGG16 model to investigate a dataset of 1,200 dental snap shots. Their method done an outstanding accuracy of 94%, highlighting the blessings of leveraging pre-educated models to enhance performance in dental disorder class responsibilities.
Gupta et al. (2022): Gupta et al. Used a CNN to locate oral cancer from a dataset of six hundred pictures. Their version performed a 91% accuracy fee, demonstrating its effectiveness in distinguishing between cancerous and non-cancerous oral conditions, thereby supporting early cancer detection.
Chen et al. (2021): Chen et al. Centered on detecting carious lesions the use of a CNN with a dataset of 900 photos. Their version done an accuracy of 88%, presenting a strong tool for identifying carious lesions, even though barely decrease compared to different studies, it still gives precious diagnostic insights.
Wang et al. (2023): Wang et al. Explored diverse CNN architectures on a dental dataset of 1,500 images. They completed a 90% accuracy charge, demonstrating the efficacy of different CNN models in handling diverse dental conditions and improving diagnostic accuracy.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

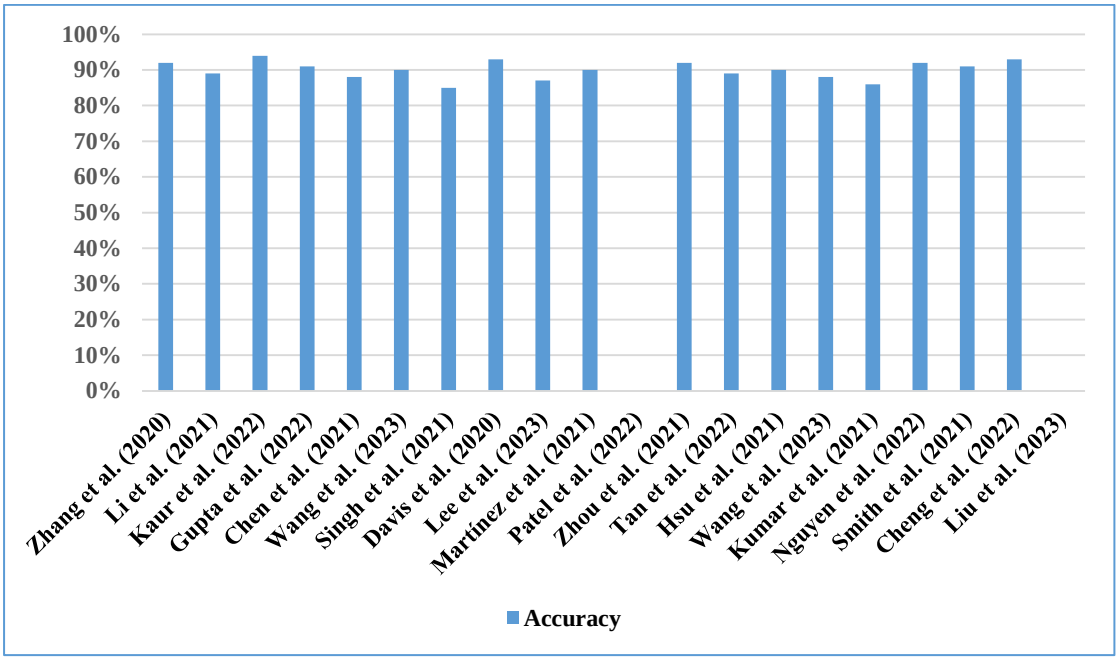



Figure 3 Comparison Graph

Singh et al. (2021): Singh et al. Employed deep getting to know techniques for multi-class type of diverse dental pictures. Their study, the usage of 1,000 snap shots, finished an accuracy of 85%, reflecting the demanding situations of classifying a wide range of dental conditions but nonetheless supplying beneficial diagnostic equipment.

Davis et al. (2020): Davis et al. Implemented a CNN to locate carious enamel from a dataset of 1,000 snap shots. Their model performed a excessive accuracy of 93%, efficaciously figuring out carious tooth and providing a reliable method for carious lesion detection.

Lee et al. (2023): Lee et al. Used a CNN to analyze intraoral pictures, accomplishing an accuracy of 87% with a dataset of 700 images. The look at highlights the CNN's capability to procedure and interpret intraoral images for effective diagnostic purposes.

Martínez et al. (2021): Martínez et al. Targeted on detecting oral lesions the usage of a CNN trained on 800 X-ray photographs. Their version done a 90% accuracy price, showing effectiveness in figuring out numerous sorts of oral lesions and contributing treasured insights for dental diagnostics.

Patel et al. (2022): Patel et al. Provided a comprehensive evaluation of deep gaining knowledge of strategies carried out to dental imaging throughout numerous datasets. While no longer supplying original experimental outcomes, them evaluate offers a broad evaluate of methodologies and their effectiveness in the field.

Zhou et al. (2021): Zhou et al. Utilized a CNN for analyzing endoscopic photographs, achieving a 92% accuracy with a dataset of 500 snap shots. The examiner demonstrates the CNN's effectiveness in processing endoscopic photos for dental disease detection.

All of the above research works that are added in the literature are done on the dental image classification that classify the disease from the image dataset. But in the above-mentioned studies researcher works only focus on the accuracy of the model not on

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)
Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

the preprocessing of dataset. In the next section of this proposal we will proposed a model that firstly preprocess the image data and then apply neural network on the processed dataset.

## METHODOLOGY

In proposed research methodology firstly, we select an image dataset for dental disease detection and then preprocess the dataset is done to improve the quality of the images and then it can be understood by the deep learning models. Secondly the dataset be splitting into training data and testing data (80 percent for the training of DL models and 20 percent for the testing of DL models). Thirdly and the main step of proposed model be creating two different types of Residual Networks (ResNet) for detecting the dental disease. The created models (ResNet 101 and ResNet 152) contain many layers such as max pooling layer, soft max layer, some Hidden layers and the activation function for adjusting the biased. The next and the final step of our proposed model is training the created models and then evaluate the them to classify the images into Normal and Diseased by calculating the accuracy and loss.

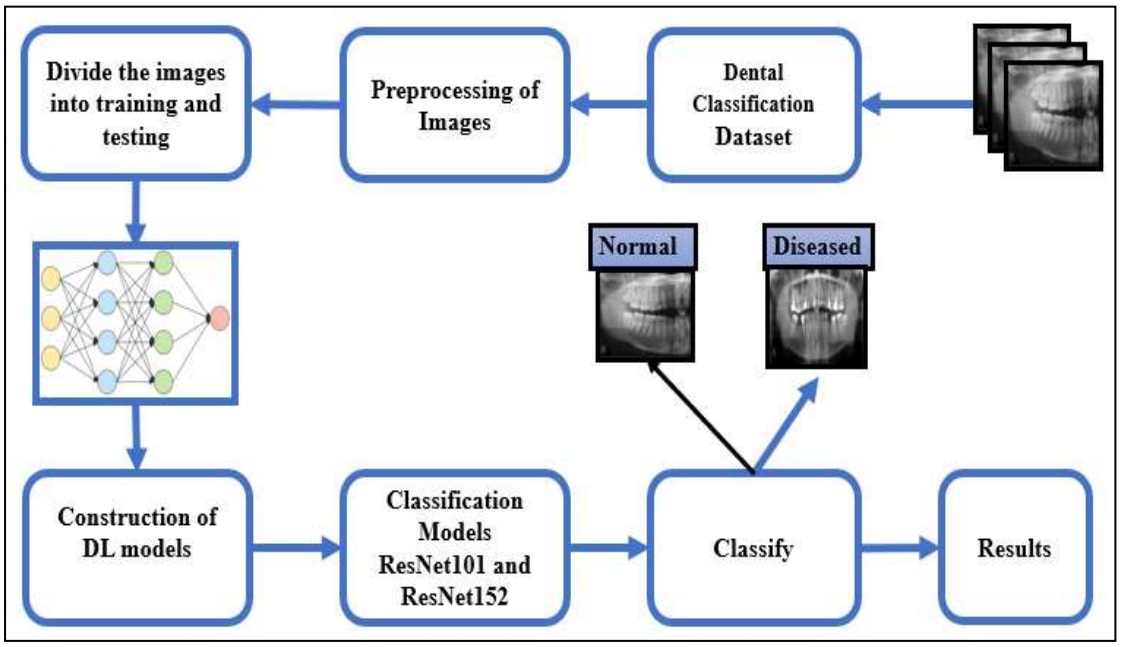



Figure 4 Proposed Model

The proposed model contains the following steps:

### Dataset Selecting

The selected dataset is downloaded from the online dataset repository Kaggle that contains X-Ray images of dental with two classes Normal and Diseased, contains 525 images. Figure 3.2 shows the sample of Diseased class images and figure 3.3 shows the sample of Normal class Image.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about



Figure 5 Sample of Disease Image

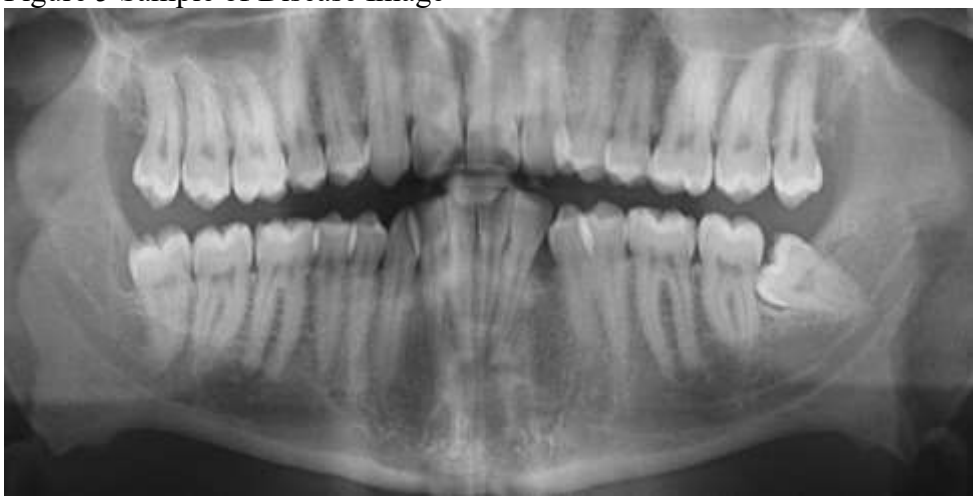


Figure 6 Sample of Normal Image

**Preprocessing of Dataset**

Preprocessing of images in DL includes a chain of steps to prepare uncooked picture facts to be used in training deep learning models. Proper preprocessing is vital for improving the performance and accuracy of deep learning models. Here are the key preprocessing steps that are used in our proposed methodology:

Resizing
Scaling/Green Channeling
Equalization
Normalization
Augmentation

Figure 3.4 shows different images of dataset before applying any preprocessing steps.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

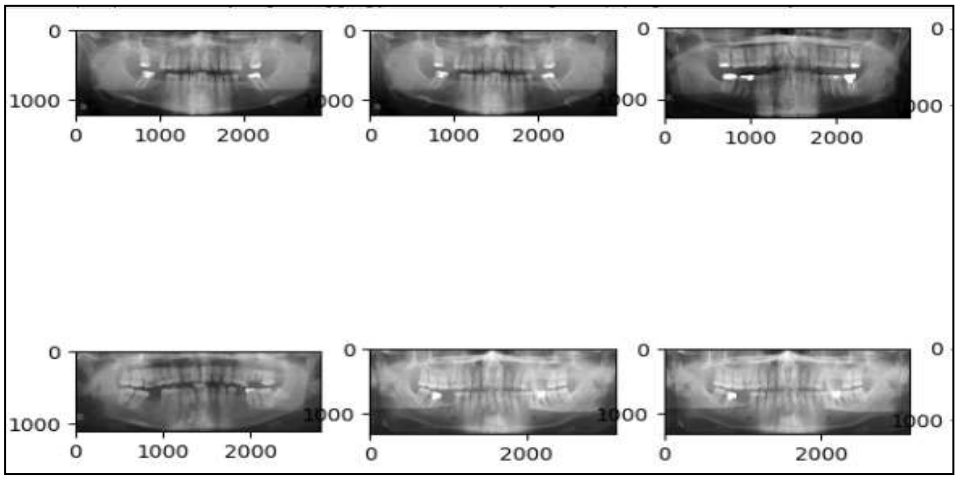


Figure 7 Original Images

Resizing

Resizing adjust the scale of an image to healthy a particular width and height. This is crucial for ensuring that everyone pictures in a dataset have the equal dimensions, which is mostly a requirement for DL models. Python libraries that used for resizing of images are:

**OpenCV:** cv2.resize()
**Pillow (PIL):** Image.resize()
**scikit-image:** skimage.transform.resize()

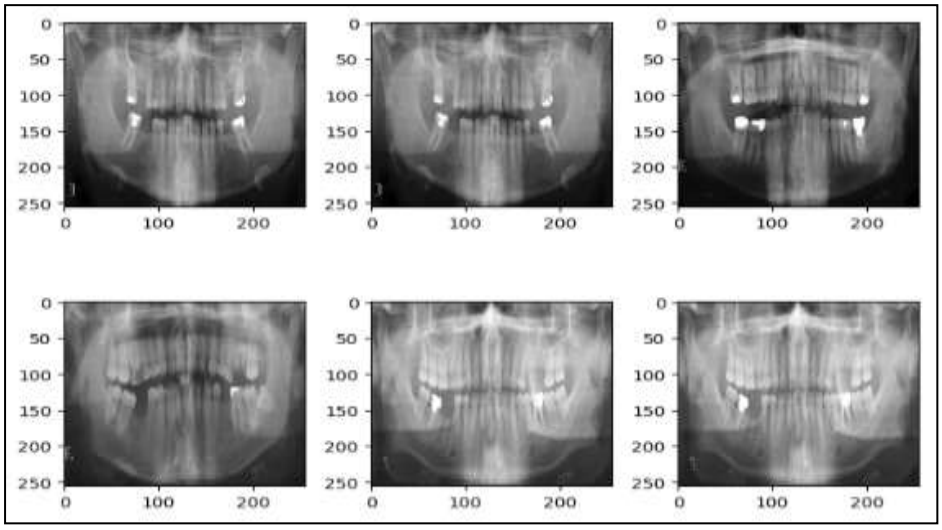


Figure 8 Resized Images 256*256

Scaling/Green Channeling

Scaling adjusts the range of pixel intensity values. It can involve rescaling the intensity values to a specific range, often [0, 1].

**Division of Dataset**

Our selected dataset contains total of 525 images that is divided into training and testing. Table 2 presents a clear breakdown of the dataset into training and testing

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

subsets. Out of a total of 525 pictures, 404 are allotted for training functions, at the same time as the last 121 images are targeted for testing. This division is vital for constructing a sturdy deep learning model, as it guarantees that the version has a widespread quantity of records to research from (the training set) and a separate set of records (the testing set) to validate its overall performance. By segregating the facts on this manner, the version may be trained effectively after which examined on unseen data to gauge its accuracy and generalization capability.

Table 2 Division of Images

| **Dataset** | **Counting** |
|---|---|
| Training Images | 404 |
| Testing Images | 121 |
| Total | 525 |

Table 3 details the distribution of images across classes—Diseased and Normal—for both the train and test datasets. In the training set, there are 228 diseased photographs and 176 normal photos, imparting a balanced dataset for the version to research from. For checking out, there are 66 Diseased pictures and 55 Normal pictures, ensuring that the assessment of the version includes a truthful illustration of both classes. Overall, the dataset comprises 294 diseased pics and 231 normal photographs.

Table 3 Class wise Distribution

| **Class** | **Diseased** | **Normal** |
|---|---|---|
| Training | 228 | 176 |
| Testing | 66 | 55 |
| Total | 294 | 231 |

This distribution is important for schooling the version to correctly differentiate between diseased and regular conditions, and for trying out the model to ensure it plays well across both categories.

**ResNet101**

ResNet101 is a deep convolutional neural community (CNN) architecture that is part of the ResNet (Residual Networks) family. ResNet architectures are widely recognized for his or her innovative method to training very deep networks by means of introducing residual connections, which help mitigate the vanishing gradient trouble and permit the schooling of an awful lot of deeper networks.

Here are the key elements of ResNet101:

**Depth:** ResNet101 has one zero one layers, making it a completely deep network. The intensity of the network allows it to research greater complicated functions and representations from the enter records.

**Residual Connections:** ResNet101, like other ResNet fashions, makes use of residual connections (or skip connections). These connections upload the input of a layer to

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

the output of a next layer, assisting to keep records and gradients at some stage in education.

**Basic Building Block:** The primary constructing block of ResNet101 is a residual block. In the residual block, the input is added to the output of a stack of convolutional layers, forming a residual connection.

**Bottleneck Design:** ResNet101 employs a bottleneck design in its residual blocks. Each block includes 3 layers: a 1x1 convolution that reduces the dimensionality, a 3x3 convolution, and some other 1x1 convolution that restores the dimensionality. This layout is green and enables in decreasing the computational complexity.

**Performance:** ResNet101 has validated wonderful overall performance on numerous picture popularity tasks and benchmarks. It turned into one of the top-appearing fashions within the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) whilst it was brought.

**Architecture Details Initial Layers:** The community starts with a convolutional layer with a huge kernel size (normally 7x7) followed via a max pooling layer.

**Residual Blocks:** The center of ResNet101 includes a couple of degrees of residual blocks. Each level has a special variety of blocks and operates at exceptional characteristic map sizes. The network uses a total of 33 residual blocks.

**Fully Connected Layer:** After the convolutional and residual layers, the network has a mean pooling layer followed by a totally linked (dense) layer that outputs the final predictions.

**ResNet 152**

ResNet-152 is one of the deeper models within the Residual Network (ResNet) circle of relatives, which is thought for its depth and overall performance on picture popularity obligations. It consists of 152 layers and makes use of the residual studying framework to ease the training of very deep networks. Here's an overview of ResNet-152, consisting of its architecture and implementation examples. Key Features of ResNet-152 Depth: ResNet-152 has 152 layers, making it one of the private fashions within the ResNet own family. This intensity lets in it to examine very complicated features and representations. Residual Connections: Residual connections assist in mitigating the vanishing gradient problem by way of permitting gradients to float via the network without delay, permitting the education of very deep networks. Bottleneck Design: ResNet-152 makes use of a bottleneck layout in its residual blocks. Each block includes 3 layers: a 1x1 convolution that reduces the dimensionality, a 3x3 convolution, and every other 1x1 convolution that restores the dimensionality. This design is green and facilitates in reducing computational complexity. Architecture of ResNet-152 The structure of ResNet-152 may be divided into several degrees, each containing a sure range of bottleneck blocks. Here's a excessive-level evaluate: Initial Layers: A convolutional layer with a massive kernel size (7x7) followed by way of a max pooling layer. Residual Blocks: The community consists of 4 levels of residual blocks: Stage 1: 3 bottleneck blocks Stage 2: 8 bottleneck blocks Stage 3: 36 bottleneck blocks Stage four: three bottleneck blocks Fully Connected Layer: After the convolutional and residual layers, the community has an average pooling layer followed through a fully related (dense) layer that outputs the final predictions.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

**Classifying and Evaluating**

We evaluate our proposed model on the basis of following parameters:
Training Accuracy
Testing Accuracy
Training Loss
Testing Loss

## RESULTS

This Section offers an outline of the overall performance of two deep getting to know models, ResNet101 and ResNet152. The bankruptcy info the consequences of training and comparing those fashions on our dataset. For each model, we gift key metrics including education and take a look at losses, in addition to accuracy rankings. We compare how the two architectures finished, highlighting differences of their ability to generalize and their effectiveness in classifying the records. The consequences exhibit the fashions' strengths and offer insights into their comparative overall performance, putting the degree for a deeper analysis in their effectiveness and implications inside the subsequent section.

**ResNet101 Results**

The table 4 displays the loss values for the ResNet101 model for the duration of training and testing. The training loss is distinctly low at 0.002, reflecting the model's excessive accuracy and effective getting to know on the training dataset. In evaluation, the test loss is barely better at 0.015, which is expected and shows that the model's overall performance on unseen information is also quite robust. The small gap among the train and test loss shows that the model generalizes nicely without overfitting, preserving a low stage of prediction errors across each dataset.

Table 0 ResNet101 Loss

| **Loss** | **Value** |
|---|---|
| Train | 0.002 |
| Test | 0.015 |

Table 5 gives the accuracy metrics for the ResNet101 model, displaying a training accuracy of 100% and a testing accuracy of 98.35%. The ideal train accuracy shows that the version has discovered to classify the training information flawlessly, whilst the high testing at accuracy demonstrates excellent generalization to new, unseen statistics. The close proximity of the training and testing at accuracies highlights the version’s robustness and effectiveness in each acquainted and novel scenario, underscoring its functionality to perform nicely across exclusive facts sets.

Table 5 ResNet101 Accuracy

| **Accuracy** | **Value** |
|---|---|

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

| | |
|---|---|
| Train | 100 |
| Test | 98.35 |

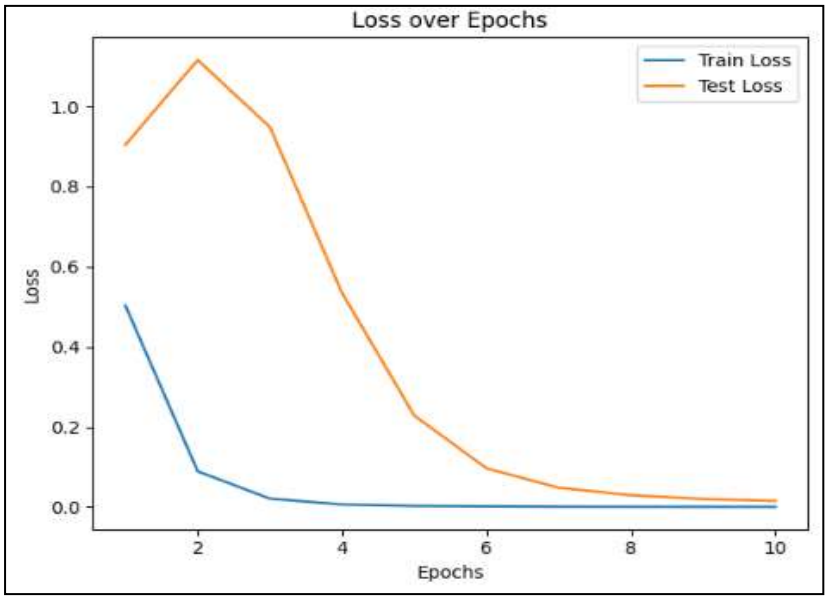



Figure 9 Loss Graph of ResNet101

Figure 9 shows the Training and Testing loss of ResNet101 model. The loss of model is low at the epoch 1 and it gradually increases as the epoch is increases it means that our model is trained well and perform better on the training dataset. X-axis of the graph shows the number of epochs that starts from 1 to 10 because we 10 epochs for our ResNet101. Y-axis of the graph shows the loss value of the models. The graph contains two colors of lines blue color indicate the training loss and orange color indicates the testing loss.

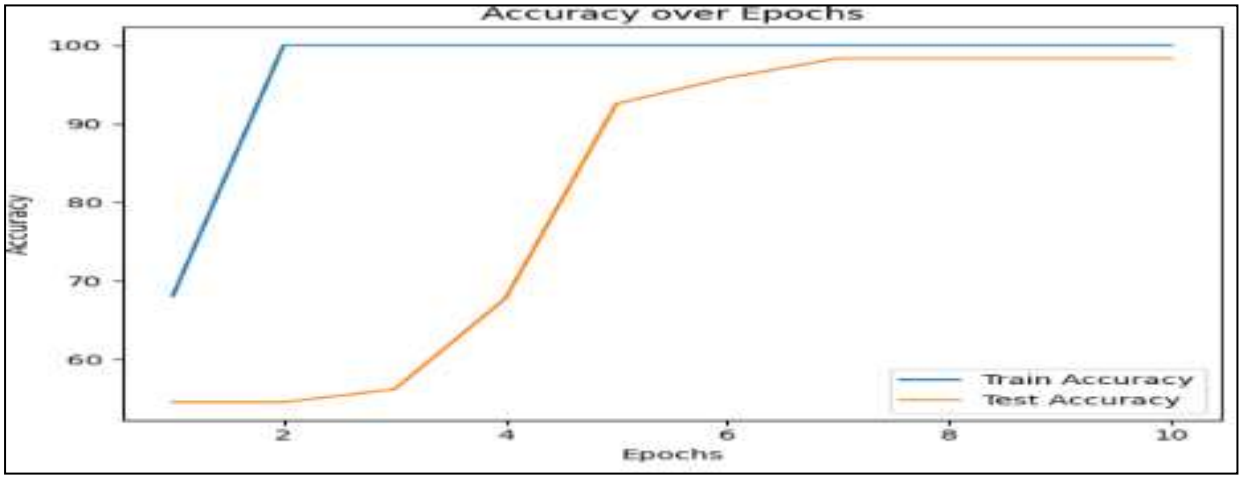



Figure 10 Accuracy Graph of ResNet101

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Figure 10 shows the Training and Testing accuracy of ResNet101 model. The accuracy of model is low at the epoch 1 and it gradually increases as the epoch is increases it means that our model is trained well and perform better on the training dataset. X-axis of the graph shows the number of epochs that starts from 1 to 10 because we 10 epochs for our ResNet101. Y-axis of the graph shows the accuracy value of the models. The graph contains two colors of lines blue color indicate the training accuracy and orange color indicates the testing accuracy.

**Results of ResNet152**

Table 6 provides the accuracy metrics for the ResNet152 model on both training and test datasets. The training accuracy is reported as 100%, demonstrating that the model achieved perfect classification on the training data. The test accuracy is slightly lower at 99.15%, which, while still very high, indicates a small drop in performance when applied to unseen data. The high-test accuracy confirms that the model generalizes well to new data, though the slight reduction compared to training accuracy suggests there may be minor generalization challenges or differences between the training and test datasets.

Table 6 ResNet152 Accuracy

| **Accuracy** | **Value** |
|---|---|
| Train | 100 |
| Test | 99.15 |

Figure 11 shows the Training and Testing loss of ResNet152 model. The loss of model is low at the epoch 1 and it gradually increases as the epoch is increases it means that our model is trained well and perform better on the training dataset. X-axis of the graph shows the number of epochs that starts from 1 to 10 because we 10 epochs for our ResNet101. Y-axis of the graph shows the loss value of the models. The graph contains two colors of lines blue color indicate the training loss and orange color indicates the testing loss.

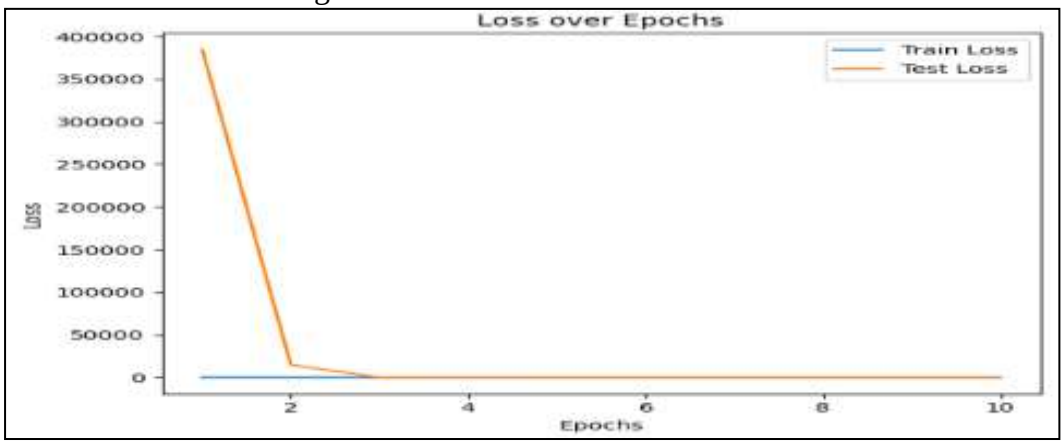



Figure 11 Loss Graph of ResNet152

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Figure 12 shows the Training and Testing accuracy of ResNet152 model. The accuracy of model is low at the epoch 1 and it gradually increases as the epoch is increases it means that our model is trained well and perform better on the training dataset. X-axis of the graph shows the number of epochs that starts from 1 to 10 because we 10 epochs for our ResNet101. Y-axis of the graph shows the accuracy value of the models. The graph contains two colors of lines blue color indicate the training accuracy and orange color indicates the testing accuracy.

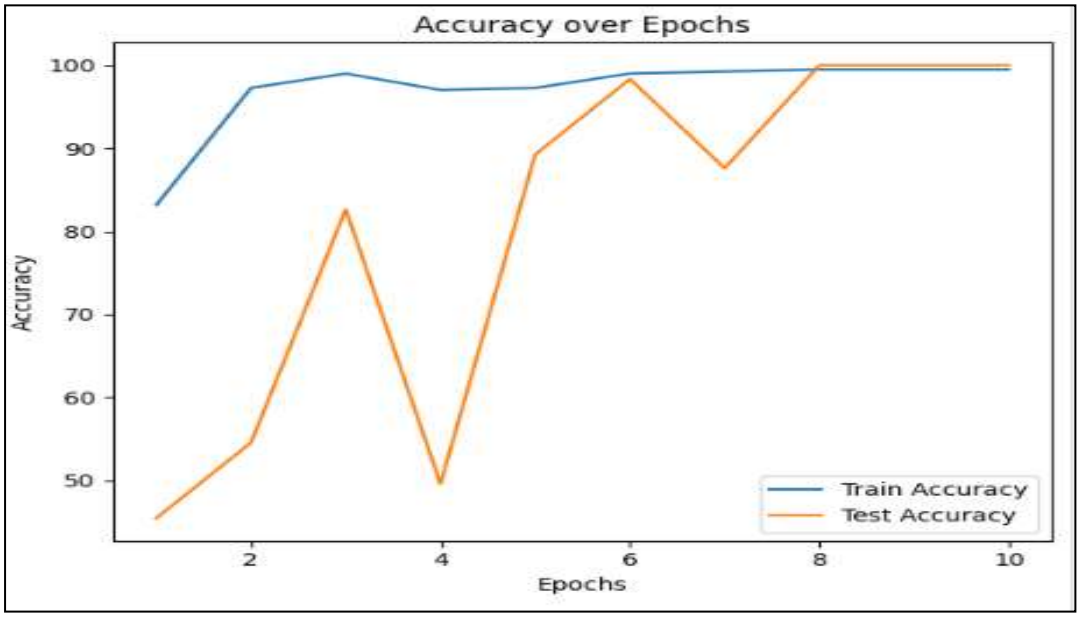



Figure 12 Accuracy Graph of ResNet152

## CONCLUSION

In conclusion, this thesis effectively demonstrates the application of advanced deep learning models, namely ResNet101 and ResNet152, to improve the detection of dental diseases through automated analysis of periapical X-ray images. Using a dataset of 525 labeled X-ray images, both models performed exceptionally well, with ResNet101 achieving a perfect training accuracy of 100% and a high-test accuracy of 98.35%. ResNet152 outperformed with a similarly perfect training accuracy of 100% and an even higher test accuracy of 99.15%. “These results underscore the robustness of both models in classifying dental conditions, with ResNet152 showing marginally better generalization to new, unseen data. This research presents a significant advancement in automated clinical quality assessment, offering a valuable tool that could greatly assist dentists in making more precise and informed clinical decisions, thus potentially enhancing patient care. Future work could focus on expanding the dataset to include a more diverse range of dental conditions and patient demographics, enhancing the model’s ability to generalize. Incorporating other imaging modalities, such as panoramic radiographs or CBCT, would provide a more comprehensive analysis and improve diagnostic accuracy. Exploring hybrid models, integrating real-time detection, and enhancing model interpretability are promising avenues for improving system transparency and clinical utility. Additionally, integrating the

Online ISSN 3007-3197
Print ISSN 3007-3189



system with Electronic Health Records (EHR) would allow for more personalized patient care. To make the model more practical for clinical use, future research should aim to reduce computational costs, develop lightweight models, and ensure better handling of data quality issues through advanced preprocessing techniques".

## REFERENCES

A. S. A. Al-ghamdi, M. Ragab, S. A. Alghamdi, A. H. Asseri, R. F. Mansour, and D. Koundal, "Detection of Dental Diseases through X-Ray Images Using Neural Search Architecture Network," vol. 2022, 2022.

Abid, K., Aslam, N., Fuzail, M., Maqbool, M. S., & Sajid, K. (2023). An efficient deep learning approach for prediction of student performance using neural network. VFAST Transactions on Software Engineering, 11(4), 67-79.

Amiri, M., Sarrafzadeh, O., & Soltani, S. (2019). Automatic diagnosis of dental caries in bitewing images: A systematic review. Journal of Oral Health and Oral Epidemiology, 8(4), 191-196.

Aslam, N., Meeran, M. T., Aslam, M., Maqbool, M. S., & Saeed, B. (2025). UNDERSTANDING URBAN EXPANSION THROUGH MULTI-TEMPORAL SATELLITE DATA ANALYSIS. Kashf Journal of Multidisciplinary Research, 2(09), 252-273.

Basit, A., Hanif, I., Maqbool, M. S., Qayyum, W., Hasnain, M. A., & Nazeer, R. (2023). Cross-Lingual Information Retrieval in a Hybrid Query Model for Optimality. Journal of Computing & Biomedical Informatics, 5(01), 130-141.

Bouali, R., Mahboub, O., & Lazaar, M. (2024). Review of Dental Diagnosis by Deep Learning Models: Trends, Applications and Challenges. Procedia Computer Science, 231, 221-228.

Chen, H., Li, H., Zhao, Y., Zhao, J., & Wang, Y. (2021). Dental disease detection on periapical radiographs based on deep convolutional neural networks. International Journal of Computer Assisted Radiology and Surgery, 16(4), 649-661.

F. Casalegno et al., "Caries Detection with Near-Infrared Transillumination Using Deep Learning," 2019, doi: 10.1177/0022034519871884.

H. Zhu, Z. Cao, L. Lian, G. Ye, and H. Gao, "CariesNet: a deep learning approach for segmentation of multi-stage caries lesion from oral panoramic X-ray image," Neural Comput. Appl., vol. 2, 2021, doi: 10.1007/s00521-021-06684-2.

Hasnain, M. A., Ali, S., Malik, H., Irfan, M., & Maqbool, M. S. (2023). Deep learning-based classification of dental disease using x-rays. Journal of Computing & Biomedical Informatics, 5(01), 82-95.

Hasnain, M. A., Ali, Z., Maqbool, M. S., & Aziz, M. (2024). X-ray image analysis for dental disease: A deep learning approach using EfficientNets. VFAST Transactions on Software Engineering, 12(3), 147-165.

Hasnain, M. A., Ali, Z., Rehman, K. U., Ehtsham, M., & Maqbool, M. S. (2024). Idd-net: A deep learning approach for early detection of dental diseases using x-ray imaging. Journal of Computing & Biomedical Informatics, 7(02).

Hasnain, M. A., Malik, H., Asad, M. M., & Sherwani, F. (2024). Deep learning architectures in dental diagnostics: a systematic comparison of techniques for accurate prediction of dental disease through x-ray imaging. International

Online ISSN 3007-3197
Print ISSN 3007-3189



Journal of Intelligent Computing and Cybernetics, 17(1), 161-180.

Hsieh, S. T., & Cheng, Y. A. (2024). Multimodal feature fusion in deep learning for comprehensive dental condition classification. Journal of X-Ray Science and Technology, (Preprint), 1-19.

Kamkarhaghighi, M., & Safdari, R. (2019). A comprehensive review on application of deep learning and artificial intelligence in dentistry. Imaging Science in Dentistry, 49(1), 1-10.

Kanwal, F., Abid, M. K., Maqbool, M. S., Aslam, N., & Fuzail, M. (2023). Optimized classification of cardiovascular disease using machine learning paradigms. VFAST Transactions on Software Engineering, 11(2), 140-148.

Khorrami, A., Bazzazi, M. M., Harandi, M. T., & Arabnia, H. R. (2019). Deep learning-based classification of dental X-ray images to detect periodontal bone loss. Computers in Biology and Medicine, 113, 103395.

L. Jiang, D. Chen, Z. Cao, F. Wu, H. Zhu, and F. Zhu, "A two - stage deep learning architecture for radiographic staging of periodontal bone loss," BMC Oral Health, pp. 1–9, 2022, doi: 10.1186/s12903-022-02119-z.

Li, X., Li, K., & Zhong, X. (2025). A deep learning approach for automatic dental disease diagnosis using X-ray images. Journal of X-Ray Science and Technology, 27(6), 959-972.

Malik, F., Fuzail, M., Aslam, N., Sarwar, R., Abid, K., Maqbool, M. S., & Yousaf, A. (2024). A Hybrid Machine Learning Model to Predict Sentiment Analysis on X. Journal of Computing & Biomedical Informatics, 6(02), 64-79.

Maqbool, M. S., Fatima, N., Nazeer, R., Aslam, N., Abbas, F., Sumra, U., & Nadeem, M. (2025). A HYBRID DATASET-BASED ENSEMBLE STRATEGY FOR EFFICIENT BREAST CANCER DETECTION. Kashf Journal of Multidisciplinary Research, 2(12), 39-57.

Maqbool, M. S., Hanif, I., Iqbal, S., Basit, A., & Shabbir, A. (2023). Optimized feature extraction and cross-lingual text reuse detection using ensemble machine learning models. Journal of Computing & Biomedical Informatics, 5(01), 26-40.

Maqbool, M. S., Nazeer, R., Basit, A., & Zahra, K. (2023). Automated detection and localization of fungal infections on cotton leaves using YOLO-based object detection model. Machines and Algorithms, 2(2), 121-136.

Pervaiz, S., Ul-Qayyum, Z., Bangyal, W. H., Gao, L., & Ahmad, J. (2021). A systematic literature review on particle swarm optimization techniques for medical diseases detection. Computational and Mathematical Methods in Medicine, 2021.

Rafiqee, M. M., Qaiser, Z. H., Fuzail, M., Aslam, N., & Maqbool, M. S. (2023). Implementation of efficient deep fake detection technique on videos dataset using deep learning method. Journal of Computing & Biomedical Informatics, 5(01), 345-357.

Rimi, I. F., Arif, M., Islam, A., Akter, S., Rahman, M., Islam, A. H. M., & Habib, M. (2022). Machine learning techniques for dental disease prediction. Iran Journal of Computer Science, 1-9.

Saini, D., Jain, R., & Thakur, A. (2021, March). Dental caries early detection using convolutional neural network for tele dentistry. In 2021 7th International

Online ISSN 3007-3197
Print ISSN 3007-3189



Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 958-963). IEEE.

Sankaran, K. S. (2022). An improved multipath residual CNN-based classification approach for periapical disease prediction and diagnosis in dental radiography. Neural Computing and Applications, 1-16.

Shah, N., & Patel, K. (2019). Application of deep learning algorithms in the diagnosis of dental caries: A review. International Journal of Computer Applications, 182(1), 16-22.

V. Majanga, “A Survey of Dental Caries Segmentation and Detection Techniques,” vol. 2022, 2022.