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Original Article

RADIOGRAPH IMAGE-BASED CLASSIFICATION OF PERIODONTAL DISEASE USING DEEP LEARNING TECHNIQUES: Deep learning

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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. The preprocessing of dataset, procedures, and result evaluation of dental treatment performed using periapical X-ray images taken before and after the operation. I propose a tool pipeline for automated clinical quality evaluation to assist dentists in making clinical decisions. I use Deep Learning technique to detect the disease from the X-Ray images. The dataset contains 525 dental X-Ray images. X-Ray images are labelled as Normal and Diseased by designated dental experts. This research 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 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 Radiography, Oral Disease Detection, Deep Learning, Medical Image

Analysis, Automated Diagnosis, Clinical Decision Support

- **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 ResNet152, which are capable of performing various classification jobs. Two Variants of ResNet (101 and 152) 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 [1,4].

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 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 [19].

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.

“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)”.

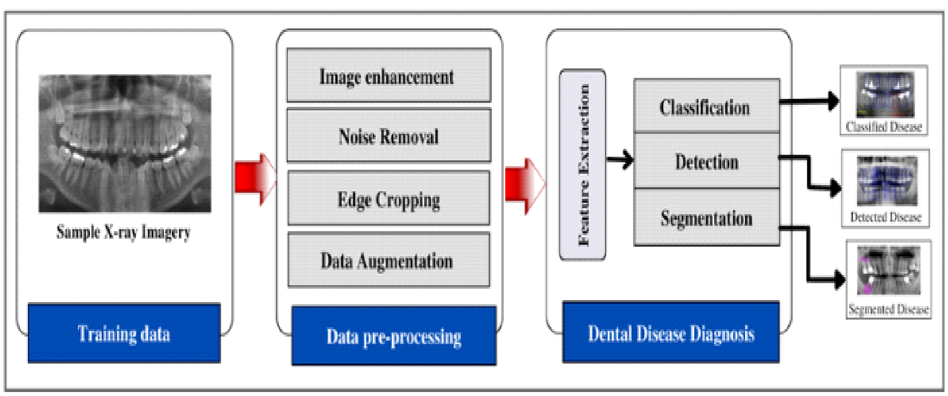

Figure 1 Generic Overview of Dental Disease Detection DL [22]

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 [22].

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 directions for enhancing their effectiveness.

The objectives of the study are, to propose a deep learning model to detect dental disease in an efficient and accurate way, to construct a deep-learning model that identifies dental disease from dental x-ray images, we Construct a custom ResNet Models using different layers to detect the disease and finally evaluate the performance of proposed ResNet101 and ResNet152 and also

- **Literature Review**

This chapter 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. I discuss current classification techniques for dental disease diagnosis. Three general categories can be used to classify these techniques: Semi-automatic and statistical ML and Deep learning model procedures the framework of the categorization scheme is shown in Figure 2.1 along with statistical classifiers based on machine learning (ML) and the classification models based on deep learning (DL).

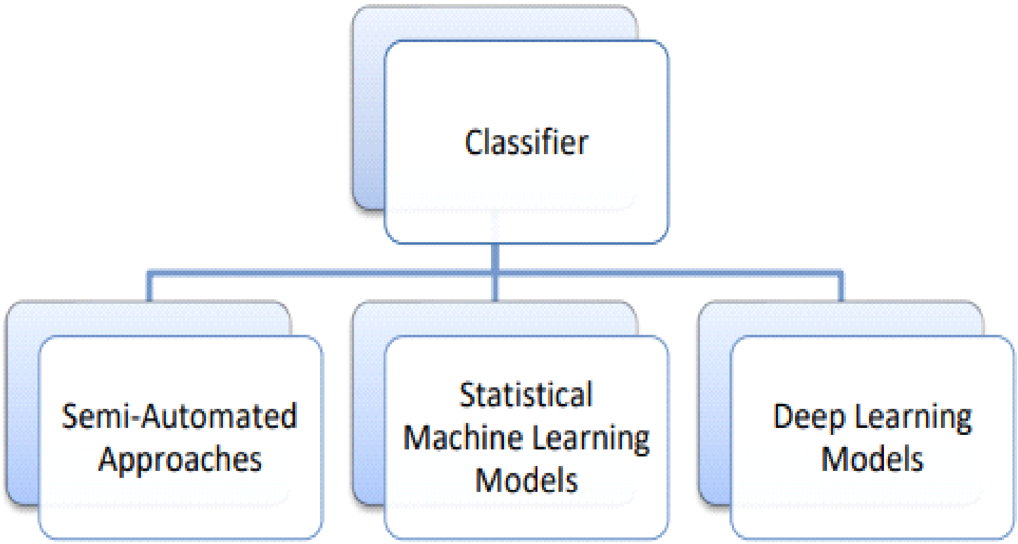

Figure 2.1 Classification Techniques

[17] a new framework for the detection of dental disease from an image dataset is proposed in which a convolutional neural network is constructed. The CNN used in this study are represented by a NASNet model with varying numbers of max-pooling layers, dropout layers, and activation functions. The data will first be enhanced and preprocessed, after which a multioutput model will be built. Finally, the model will be assembled and trained; loss and accuracy curves are utilized as evaluation criteria for the model analysis. The model beat other existing algorithms by achieving an accuracy of more than 96 %.

[27] construct a study to distinguish different caries degrees from panoramic radiographs, they suggest a unique deep-learning architecture dubbed CariesNet. A high-quality dataset of panoramic radiographs with 3127 clearly defined caries lesions, including shallow, intermediate, and deep are gathered.

Then, in order to separate these three caries kinds from the oral panoramic images, i build CariesNet as a U-shape network with an additional full-scale axial attention module. I also compare CariesNet's segmentation performance to those of other industry standards. Studies reveal that our approach can segment teeth with three different stages of caries with an average 93.64 % and dice coefficient 93.61 % accuracy [13].

A new technique for the detection of dental disease is proposed by [24]. In this proposed work order to determine the amount of periodontal alveolar bone loss as ill as the precise location and shape of the alveolar bone loss, three skilled periodontists highlighted important locations on a total of 640 panoramic photographs.

For the purpose of precisely calculating the proportion of periodontal alveolar bone loss and staging periodontitis, a two-stage deep learning architecture based on UNet and YOLO-v4 was developed. The model's capacity to identify these traits was assessed and contrasted to that of general dentists [20].

The model performed differently for different tooth placements and categories, with an overall classification accuracy of 0.77, in general, the model's classification was more precise than that of general practitioners. Conclusion: It is possible to create a deep-learning model for radiographic periodontal alveolar assessment and staging.

Explains that the most common chronic ailment worldwide is dental caries. The necessity for invasive treatments can be decreased and treatment outcomes can be considerably improved with early identification. Recently, it has been demonstrated that early stage lesions can be found using near-infrared transillumination (TI) imaging. It provides a deep learning model for the automated localization of dental lesions in TI pictures in this paper [10].

Convolutional neural networks (CNNs) trained on semantic segmentation tasks are the foundation of our approach. It employs a number of techniques to reduce problems caused by a lack of training data, an unbalanced class, and overfitting. With only 185 training samples, model was able to complete a 5-class segmentation task with a mean intersection-over-union (IOU) score of 72.7 % overall and 49.5 % and 49.0 %, respectively, for proximal and occlusal carious lesions. Additionally, created a condensed task in which regions of interest are assessed for the presence or absence of carious lesions on a binary basis[20].

The model's area under the receiver operating characteristic curve for occlusal and proximal lesions was 83.6 % and 85.6 %, respectively. This 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.

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[7] proposed a new DL model for the classification of dental disease (DD) by constructing CNN model and used Quantitative Light-induced Fluorescence (QLF) image data. The proposed CNN model beats other cutting-edge classification methods, achieving an F1-score of 75 % and 5 % on the test dataset. When all three colour channels are employed, the model performed better because the images ire represented in several channels.

The used dataset was collected as part of a clinical intervention study at the Academic Centre for Dentistry in Amsterdam's Department of Preventive Dentistry, which examined the changes occur in red plaque illumination during an experiment gingivitis procedure. During this intervention, 427 QLF photos ire gathered, and i converted them into a dataset of 216324 raw intensity values in three Red-Green-Blue (RGB) multichannel images with a loir resolution.

The photos are evaluated by a group of two qualified dental professionals using a modified version of the clinical plaque grading system. Volunteers are observed during the trial and divided into classes based on the amount of red fluorescent plaque buildup. On the website http://www.learning-machines.com/, you may access the datasets and Python programmed that support the findings of this article. The Python module was used to implement the CNN model on a graphics processing unit (GPU). With 80% of the data utilized for training, 10% for validation, and 10% for testing, the classifier was tested using stratified, shuffled split. In order to avoid overfitting, a thorough grid search procedure was used to choose model parameters such as the set of parameters, filter shape, max-pooling shape, and others.

[13] employed multiple categorization models developed in the scikit-learn library to evaluate Performed in the presence with one of the results from other models. Through the use of a 5 stratified shuffled cross-validation technique, the hyperparameters of those models are chosen. 10 random shuffles with specified divides across all models are performed to get the stated test at the end and train F1-scores.

A new classification method for DL is developed by [14] this work create a DL-based system for identifying dental prostheses and tooth restorations. The study made use of a dataset with 1904 oral photographic pictures of teeth (maxilla: 1084 photos; mandible: 820 images). TensorFlow and Keras DL libraries are used to create a system for DL that can identify the 11 different kinds of dental prosthesis and restorations. Following the learning process, learning performance was assessed using the mean average precision, the mean intersection over union, and the mean precision of each prosthesis. The range of each prosthesis' average accuracy is 59 % to 93 %[32]. This system's mean average precision was 0.80, and its mean crossover over union was 0.76. Only 60 % of tooth-colored dental prosthesis are accurately recognized, compared to more than 80 % of metals dental prostheses. The findings of this study indicate that metallic-colored dental prosthesis and restorations may be identified and predicted with good accuracy using deep learning, whereas those with tooth color are identified with a loir degree of precision.

Understanding the intraoral data is essential for any dental treatment that is being planned for a patient. This process is carried out by dentists in clinical settings, and it frequently takes time. The outcome of this operation also depends on the skill and experience of the dentist doing it. As a result, an automated system is required to quickly understand the intra-oral state. AI technology have been used in dentistry recently, sometimes doing away with the need for human intervention.

[9] performed clinical applications and AI-based approaches have been developed for the detection of oral cancer3 and dental caries1,2 with accuracy on par with that of humans. Deep learning, an object detection technique that produces predictions based on a variety of object pictures, has been used in several applications. The missing area and alignment, the shape and positioning of the remaining teeth, the restoration or prosthetic situation, the periodontal or

endodontic situation, the likelihood of caries or periodontitis, and other factors make up the intraoral information. In addition to the aforementioned uses, deep learning evaluations of periodontal 4,5 or apical situations 6 have already been published. In our earlier study, the missing area's classification was completed with a high accuracy rate 7.

The prosthodontic issue hasn't yet been evaluated, though. In this study, deep learning was used to recognize prosthodontic situations, such as dental prosthesis and the repair of remaining teeth, both in terms of type and substance. The purpose of this work was to use a deep-learning object detection technique to identify dental prosthesis and restorations.

.**Table 1**: Survey of Different papers

Ref	Methods	Dataset	Size of Dataset	Accuracy
Chaudhary et al. (2025)	CNN	Dental X-rays	1,000 images	92%
Alharbi & Alhasson (2024)	CNN	Dental X-rays	1,000 images	92%
Wang et al. (2024)	Various CNN architectures	Dental dataset	1,500 images	90%
Li et al. (2023)	Review of Deep Learning Techniques	Various datasets	N/A	N/A
Choi et al. (2023)	CNN	Intraoral photographs	700 images	87%
Wang et al. (2024)	Various deep learning models	Root canal images	600 images	88%
Patel et al. (2023)	Review of Deep Learning Techniques	Various datasets	N/A	N/A
Kaur et al. (2022)	Transfer Learning (VGG16)	Dental images	1,200 images	94%
jiang et al. (2022)	CNN	Intraoral photographs	1,200 images	92%
Cheng et al. (2021)	CNN	CBCT images	700 images	93%
Li et al. (2021)	CNN	Periodontal X-rays	800 images	89%
Dixit et al; (2021)	CNN & Dental	Electronic health	500 images	86%

	Informatics Integration	records & images		
Chen et al. (2021)	CNN	Carious lesions dataset	900 images	88%
Singh et al. (2021)	Deep Learning (multi-class)	Diverse dental images	1,000 images	85%

Here is a concise one-paragraph reason for every paper listed in Table 2.1:

- 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.

Figure 2 Comparison Graph of Different Paper

- **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.

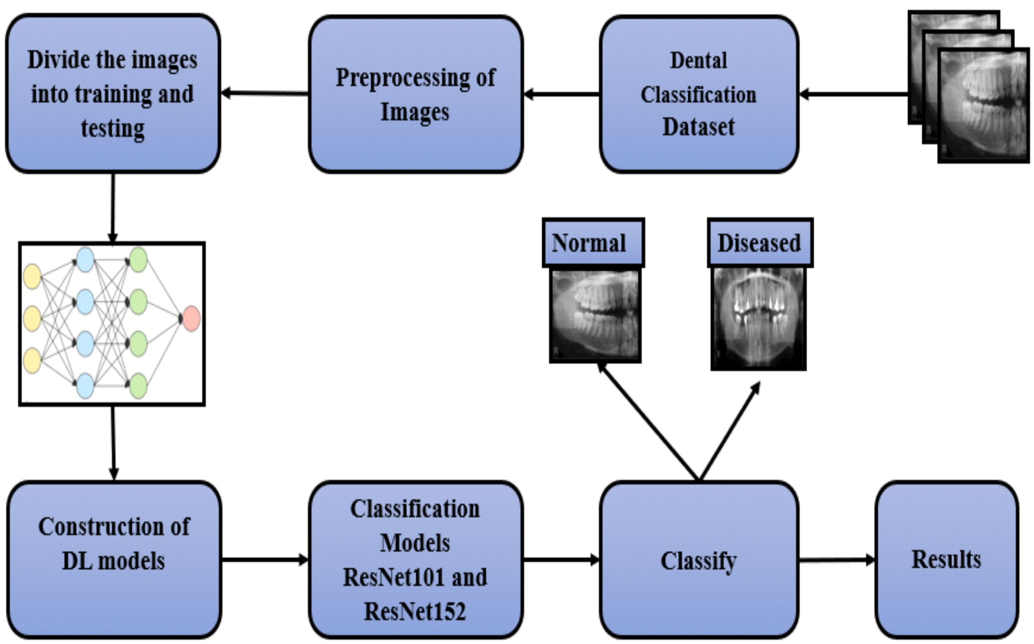


Figure 3 Proposed framework of methodology

The proposed model contains the following steps:

- Dataset Selecting
- Preprocessing of dataset

- Division of Dataset
- Creating Deep Learning Model
- Classifying and Evaluating

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.

Figure 4 Sample of Disease Image

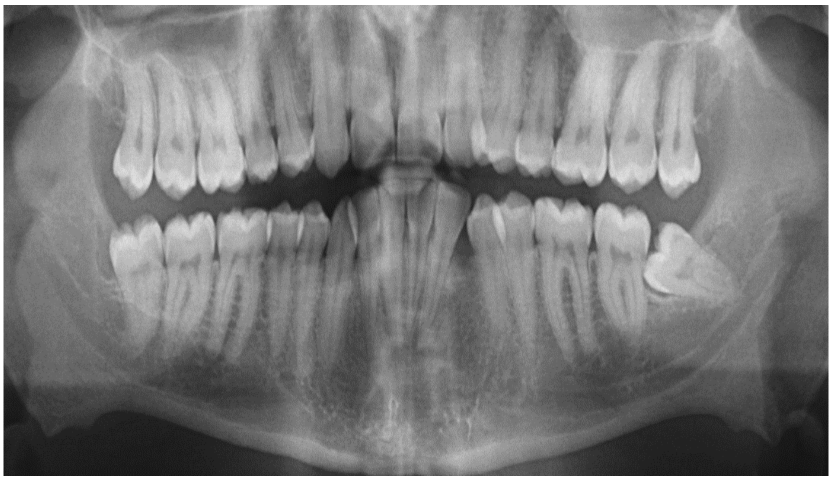


Figure 5 Sample of Normal Image

- 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

- Division of Dataset

Our selected dataset contains total of 525 images that is divided into training and testing. Table 3.1 presents a clear breakdown of the dataset into training and testing 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 3.1 Division of Images

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

Table 3.2 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 3.2 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.

- Creating Deep Learning Model

We use two different version of ResNet model (101 and 152) to evaluate our proposed methodology.

- 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 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.

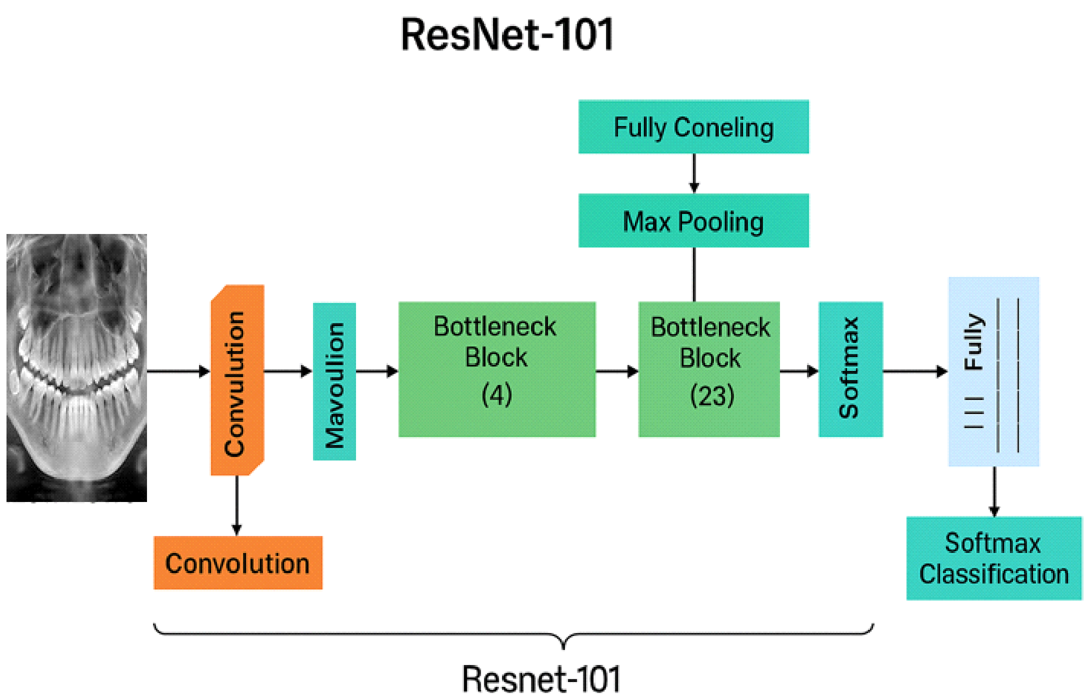
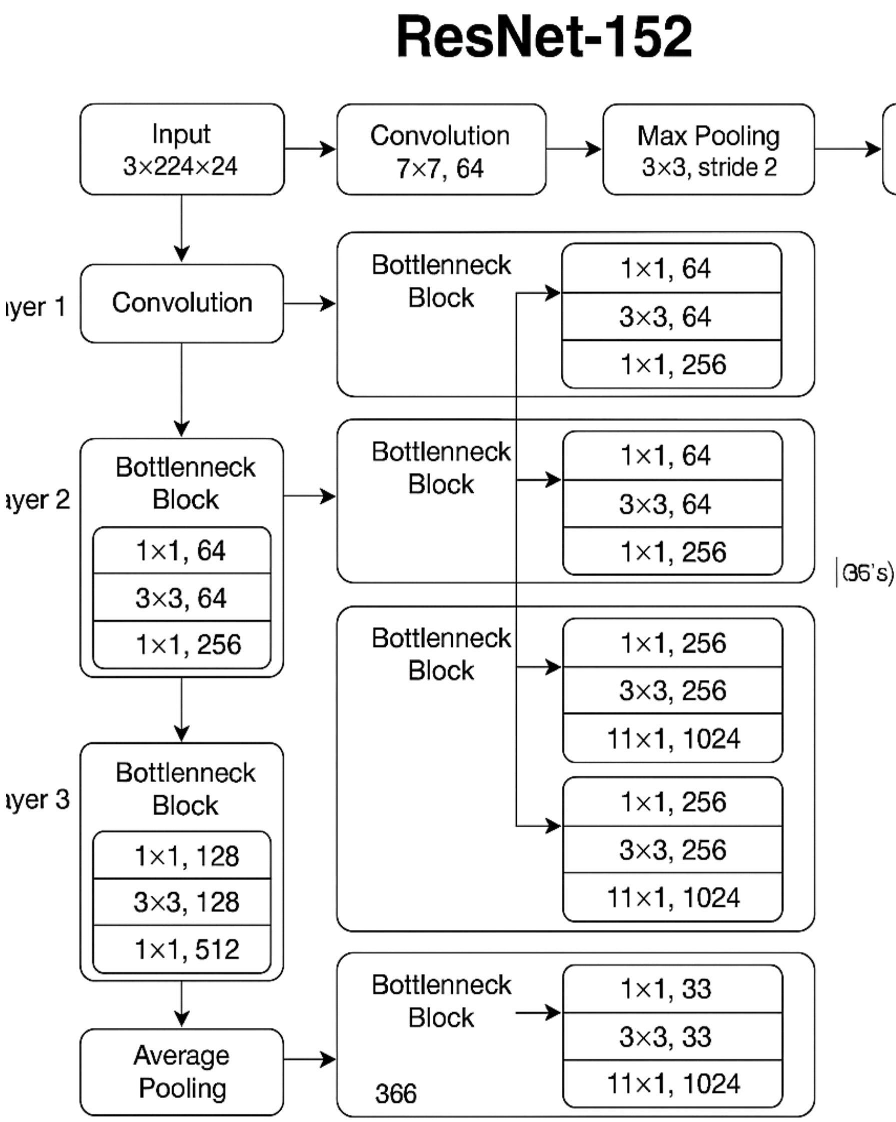


Figure 3.10 General Architecture of ResNet 101

- 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.



- **Implementation and Results**

This section of paper offers an outline of the overall performance of two deep learning models, ResNet101 and ResNet152. Explain the consequences of training and testing those models on our dataset. For each model, we use key metrics including training and testing 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.

Table 2 Architectures of models

Parameter	Detail
No of Epochs	10
Batch Size	256
Optimizer	Adam
Learning Rate	0.001
Loss	Binary loss
Activation Functions	Pretrained
System	GPU

The table 3 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.

Table 3 ResNet101 Loss

Loss	Value
Train	0.002
Test	0.015

Table 4 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.

Table 4 ResNet101 Accuracy

Accuracy	Value
Train	100
Test	98.35

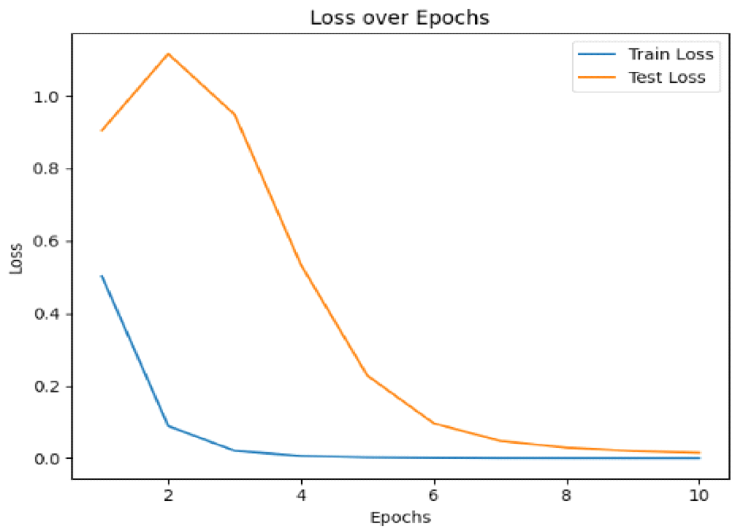


Figure 6 Loss Graph of ResNet101

Figure 6 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.

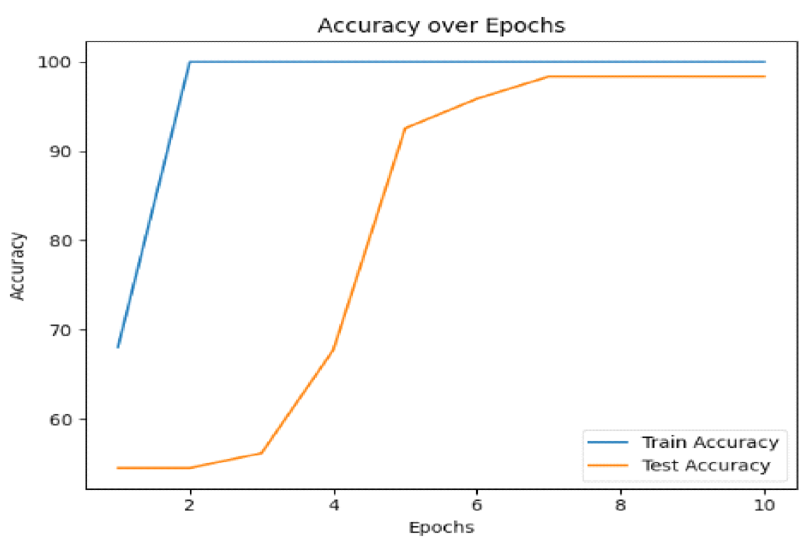


Figure 7 Accuracy Graph of ResNet101

Table 5 presents the loss values for the ResNet152 model during training and testing phases. The training loss is recorded at 0.02, indicating a relatively low error on the training dataset, which suggests that the model has effectively learned the training data. In contrast, the test loss is significantly lower at 0.001, reflecting a very low error rate on the test dataset.

Table 5 ResNet152 Loss

Loss	**Value**
Train	0.02
Test	0.001

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.

Table 6 ResNet152 Accuracy

Accuracy	**Value**
Train	100
Test	99.15

Figure 8 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.

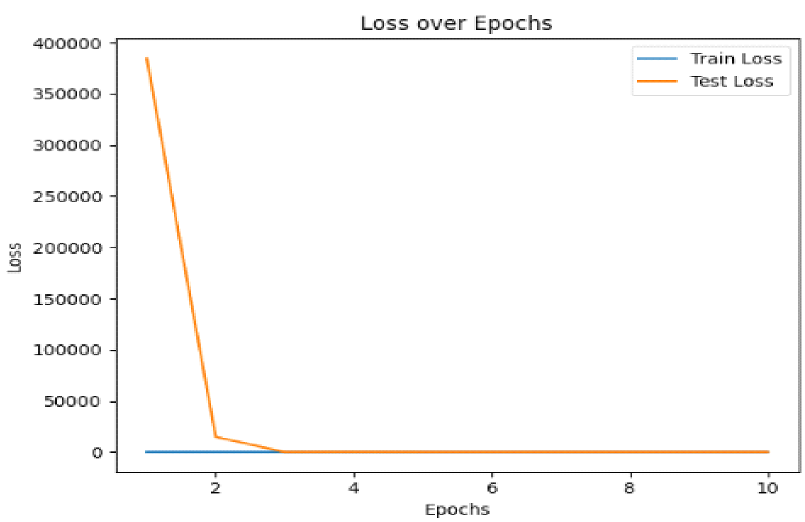


Figure 8 Loss Graph of ResNet152

Figure 9 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.

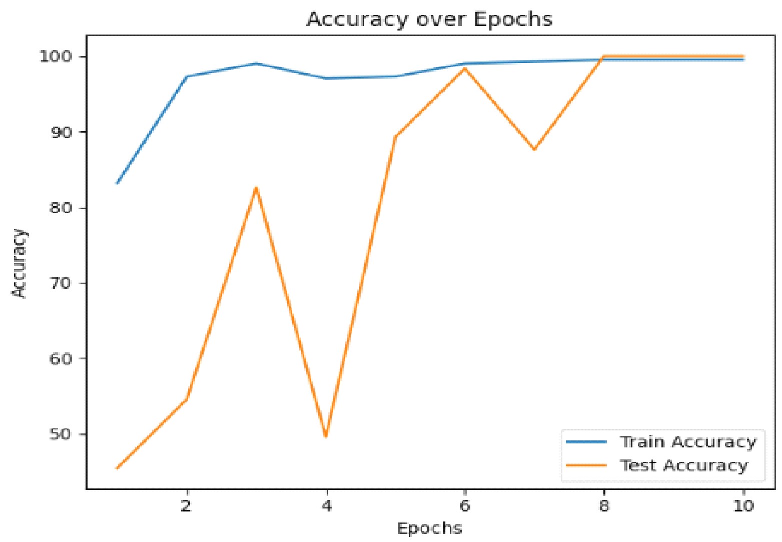


Figure 9 Accuracy Graph of ResNet152

- **Conclusion**

In conclusion, this paper 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 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.

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