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Classification and Segmentation of Periodontal Cyst for Digital Dental Diagnosis Using Deep Learning

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The digital revolution is changing every aspect of life by simulating the ways humans think, learn and make decisions. Dentistry is one of the major fields where subsets of artificial intelligence are extensively used for disease predictions. Periodontitis, the most prevalent oral disease, is the main focus of this study. We propose methods for classifying and segmenting periodontal cysts on dental radiographs using CNN, VGG16, and U-Net. Accuracy of 77.78% is obtained using CNN, and enhanced accuracy of 98.48% is obtained through transfer learning with VGG16. The U-Net model also gives encouraging results. This study presents promising results, and in the future, the work can be extended with other pre-trained models and compared. Researchers working in this field can develop novel methods and approaches to support dental practitioners and periodontists in decision-making and diagnosis and use artificial intelligence to bridge the gap between humans and machines.

Keywords: CNN, classification, dental radiographs, deep learning, health care, machine transfer learning, periodontal cyst, predictive analytics, segmentation, U-Net, VGG16.

1. Introduction

Gum diseases are widespread chronic infectious dental disorders that affect the majority of adults across the world [36]. The symptoms of gum diseases are generally exhibited in advanced stages. Periodontal disorders are common chronic inflammatory illnesses that damage the teeth's supporting tissues. Periodontal disease, if left untreated, will affect the other parts of the body causing cancer and respiratory diseases [3]. According to the Centers for Disease Control, periodontal disease affects 47.2 percent of persons aged 30 and older in the United States and the Prevention periodontal disease surveillance project carried out a survey on periodontitis [10]. Periodontitis is the most common chronic inflammatory disease affecting the global population. If not addressed in time, it results in decay of bone and tooth loss. Periodontitis worsens the tooth structure gradually, which results in complete tooth loss and other severe consequences if not diagnosed properly at the right time. The most probable reason for periodontitis is poor oral hygiene. A pocket can form behind the gum line, trapping leftover food particles as result of chewing without proper brushing, which results in the accumulation of bacteria. This results in plaque. If plaque is not cleaned, it becomes hard tartar that is difficult to remove. It spreads deep into the gums, slowly causing gingivitis. If it is not treated, the bacteria spreads slowly deeper into the gums toward the root causing alveolar bone loss. The supporting hard and soft tissues are also affected, and the tooth becomes loose causing its high mobility leading to tooth loss.

Gum disease begins with inflammation in gums where discoloration of gums occurs, resulting in bone loss, supporting structure loss and finally tooth loss. The severity of the disease is assessed based on clinical radiological findings such as periodontal pocket depth, bleeding on probing, clinical attachment loss, furcation, black triangles, and alveolar bone loss. It is not just oral disease. Many researchers and studies have shown other systemic diseases associated with periodontitis such as cardiovascular diseases, Alzheimer disease, diabetes, adverse pregnancy outcomes, respiratory infections, arthritis, oral carcinoma and gastrointestinal disease [4]. Dental cysts, abscesses and tumors are other major oral diseases that worsen the patient's condition by spreading rapidly if left unattended. Periodontal disease is associated with several risk factors such as age, socioeconomic status, race and gender, smoking, genetic factors, systemic disease, stress, obesity, alcohol and others [26, 28]. Regular dental check-ups with appropriate treatment and cleaning may decrease the severity and stop the progression of periodontitis. Oral disease such as caries can be easily identified by teeth discoloration even by a layman and it can be immediately treated with the help of a dentist, but periodontitis is not the case. By the time the patient experiences symptoms, there might be chances that internal destruction of the tooth might have started. Also, the cost of treating periodontitis is a little more expensive than the cost of treating caries. The tooth damage is also more significant in the case of periodontitis than the damage because of caries. Since all these deficiencies are identified, there is a need for computer-assisted prediction and analysis methods to deal with these diseases.

Recently, computer-aided diagnostics (CAD) based on deep learning have been widely employed in radiology to solve challenging issues [7]. Machine learning and deep learning, the subsets of artificial intelligence, take the lead in all the fields during the current computer era, and the former requires domain expert knowledge to identify features and the latter understands features incrementally without the expert's interference. Compared to machine learning, deep learning needs high-performance GPUs, computational power and a large volume of data to give appropriate results. One of the major application areas of deep learning includes predicting, classifying and segmenting medical images [38]. According to research studies in the past, machine learning and deep learning have been successfully implemented for periodontal disease prediction, classification, and cyst detection [25]. Where human experts' intervention was previously needed it is now being replaced by artificial intelligence and its subsets [31]. Machine learning and deep learning are extensively used in dentistry for caries detection, periodontal disease prediction, cyst/tooth segmentation, prediction of end lesions, diagnosis of tooth fracture, predicting restoration failure, implant dentistry, clear aligners, designing dentures, tooth shade selection and many more [16, 19, 35]. Many deep learning models have been successfully implemented and obtained promising results in object localization, segmentation and prediction process [5]. As there is a need to implement digitization in dentistry and allied fields, the researchers focus on applications of the machine and deep learning models to solve these problems from which various models and tools developed that can serve as helping aids for dentists. This paper focuses on periodontal cyst classification, prediction models and periodontal cyst segmentation models using convolutional neural network (CNN), visual geometry group 16 (VGG16) transfer learning and U-Net models. As the quality of predictions depends upon the quality of input data, pre-processing steps play a significant role in the machine and deep learning models.

In this work, a pilot study on 600 images is conducted initially and then extended to 10 000 images and a detailed analysis is performed on predicted outputs. The radiographs for the entire study are collected from the KT Super Speciality Dental Hospital in Tirupati, Andhra Pradesh, India with proper consent and approval. The first part of the work focuses on periodontal cysts classification using a CNN and pre-trained VGG16 with convolutional base models, and in the second part of the work, periodontal cysts images are collected and U-Net is implemented to segment objects in the image. The segmentation process is implemented in two ways: in the first method, a pure U-Net model is implemented, and, in the second method, the ResNet backbone and ImageNet weights are used for the segmentation process. The main objectives of the paper are as follows:

- To investigate and review the literature related to CNN, VGG16, U-Net and other machine and deep learning models in order to come up with the missing links in the research;
- To implement a CNN for classifying images with periodontal cysts and no cysts;

- To implement transfer learning with VGG16 to enhance the classification accuracy of CNN;
- To implement segmentation on dental images using U-Net to identify cyst areas;
- To compare all the results obtained in terms of efficiency/accuracy.

2. Literature review

Artificial intelligence, machine and deep learning techniques are widely used nowadays in medical/dental diagnosis, disease prediction and analysis. Much automatic detection of oral diseases has been devised and enhanced over the last few decades. As there are several notable researches in this area, the implementation of such technologies in dentistry is presented in this section.

Miki *et al.* [29] used a deep convolutional neural network for the classification of teeth to automate dental filling in the Caffe network using AlexNet on two datasets, one with augmented images and the other without augmentation, and achieved an accuracy of around 91% and concluded that classification could be used to differentiate different types of teeth such as incisors, molars, premolars and canines without the need for segmentation.

Hwang *et al.* [17] presented applications of deep learning model in areas of dental specializations where convolutional neural networks and other pre-trained models such as ResNet, AlexNet, ImageNet, GoogLeNet, VGG, etc. were used in the classification of the tooth segmentation, dental plaque assessment, caries detection, periodontal disease classification and other medical applications.

Kim *et al.* [24] took dental radiographs as input and implemented deep CNN with transfer learning to detect periodontal bone loss on 12 179 images. Also, teeth segmentation in regions of interest was implemented and achieved better results.

Moriyama *et al.* [30] used a CNN and MapReduce algorithm to identify the tooth and its coordinates. Then, pocket region images were given as input to the CNN classifier and the pocket depth was obtained as output. In the mapping phase, the teeth and pocket regions were identified. In the classification phase, the mapping phase output was provided as its input to CNN and the pocket depth was obtained, and in the reducing phase, the final aggregate of pocket depth value was obtained.

Rana *et al.* [37] used a deep learning model with an autoencoder framework, and convolutional and max pool layers for automated segmentation of inflamed gingiva around the teeth using 405 images. The input images, the respective annotations and masks were given to the classifier with dice loss function and the model was trained with adaptive gradient descent with momentum, and the obtained precision and recall values were 0.347 and 0.621, respectively.

Sivasundaram and Pandian [42] worked on CNNs to segment and classify different dental cysts on 1171 dental images annotated by expert radiologists. Data augmentation was performed to increase the image dataset. The authors used modified LeNet architecture with convolutional and max pool layers to classify cysts and obtained 99.55% accuracy in classifying dentigerous cysts, 99.43% accuracy in classifying odontogenic cyst, and overall accuracy of 99.63%, precision of 99.75%, and F-score of 98.9 were obtained.

Yang *et al.* [46] implemented a deep learning-based segmentation system for different oral cysts and tumors. They used the YOLO (you only look once) v2 algorithm for classification and segmentation.

Schwendicke *et al.* [41] presented a review on the number of research works done in various fields of dentistry using deep learning models. According to their survey, studies implementing convolutional neural networks were successful in detecting lesions, teeth, osteoporosis, cephalometric landmarks, periodontitis, alveolar bone loss, periodontal pockets, age, sex and many other applications in dentistry.

Zhang *et al.* [47] introduced a self-learning segmentation model using U-Net on a Caffe framework recursively as level 1, 2 and 3 trained for 50k iterations. The model performance was cross-checked with manual evaluation on one slice, which consumes much time to do manually. Therefore U-Net gave better results in the segmentation of images.

Orhan *et al.* [32] worked on the implementation of artificial intelligence to identify periapical lesions. Manual identification of lesions was then compared with lesions identified by implementing deep CNN. The model provided better results in detecting teeth and their numbering.

3. Proposed methodology

Periodontitis, the most affecting oral disease in the global population, has a serious impact on the overall health of an individual if not properly treated in time [2]. The disease is related to gums. It is also associated with other systemic diseases and risk factors such as stress, obesity, smoking, alcohol consumption, poor oral habits, nutrition, medications, etc. [12]. If the disease is not identified and treated early, it results in bone and tooth-supporting structure loss, finally leading to tooth loss [15]. There are other pathologies affecting the human tooth, such as cysts, tumors and abscesses. There are various dental cysts such as radicular cyst, residual cyst, dentigerous cyst, lateral periodontal cyst, odontogenic keratocyst, primordial cyst and Gorlin cyst [14], but the present study focuses on the lateral periodontal cyst. There are more chances of spreading the infection from one area to another area within the mouth if the cysts are not identified and treated early. Apart from the spreading of infection, the treatment costs also increase and the severity of damage to the tooth will also be high if not diagnosed at the right time in the initial stages. By the time the patient experiences the symptoms such as pain, swelling, bleeding and other symptoms, the impact of the disease on the tooth might start. Since there is a need for early prediction, the proposed study focuses on the classification segmentation of periodontal cysts to support dentists in timely decision-making. If the disease is not treated in time, the severity progresses rapidly, increasing treatment costs and complications.

Therefore, to bridge these gaps, computer-assisted models are necessary. In the current study, CNN, VGG16 and U-Net models are used. Usually, in CNN, there will be 5–10 layers whereas, in deep CNN, the number of layers will be higher. Since there are more layers, there is a probability of an increase in overall performance in deep networks and one such architecture is VGG16 with 16 layers. As it has been proved that VGG16 performs well among all the other architectures on the ImageNet dataset, CNN and VGG16 models are considered in the proposed research to study periodontal cysts images. In the present work, radiographs of patients with and without periodontal cysts are collected, all the images are pre-processed to the same size and mode using Image J, and data augmentation is performed to avoid over-fitting. The final images are given to a CNN for the classification of radiographs with and without cysts. Later, to enhance the classification accuracy, transfer learning with VGG16 is implemented and improvised results are obtained. Once classification is completed, the work continues with the segmentation part. U-Net architecture is implemented in two ways: a simple U-Net, U-Net with ImageNet weights and ResNet backbone. As a result, semantic segmentation of radiographs is obtained.

3.1. Data acquisition and pre-processing

The present work focuses on the classification of radiographs with a periodontal cyst and radiographs with no periodontal cyst using CNN. Also, segmentation using U-Net is performed to identify areas in the image with a cyst. For the current study, panoramic dental radiographs with cysts and without cysts are collected from K T Super Specialty Dental Hospital with doctor consent and approval. In this study, 10 012 panoramic dental radiographs are considered, of which 3905 are radiographs with a periodontal cyst and 3917 with no periodontal cysts, 7822 images were used for training. For validation, 996 with cyst and 996 with no cyst, providing in total 1992 images. For testing, 96 with cyst and

102 with no cyst, a total of 198 radiographic images are used. All the original radiographs are rescaled to 224×224 sized RGB images using the Image J tool for uniformity. Data augmentation is also done. For U-Net method 1 implementation, 10 000 RGB panoramic images containing cyst are used rescaled to 128×128, and for method 2 implementation, 10 000 256×256 sized RGB images and the respective binary masked images are considered.

3.2. CNN-based periodontal cyst classification

CNNs, the most efficient and useful technology in various research areas of computer vision, have achieved tremendous results in medical/dental applications [45] such as cancer detection [8], automated segmentation of liver and kidneys [9], brain tumor grading [33], detection of myocardial infarction [1], urinary bladder segmentation [6], diabetic retinopathy [34], caries detection [39], teeth segmentation [44], lesion detection [11], periodontal disease detection [27]. As there are many components and requirements for early predictions and detections of periodontitis, in the current work, CNN-based classification of periodontitis is implemented. To implement and build this deep learning model, TensorFlow 2.3.0, Keras 2.4.3, the server of Jupyter notebook 6.4.0 running with Python version 3.8.10, and other data science and machine/deep learning libraries and packages are used from Keras with TensorFlow backend. The VGG16 pre-processing function is used in coding for uniform pre-processing of all input images. The CNN model is built with 10 convolutional layers, including an input layer and 5 max-pooling layers with 3×3 kernel. During compilation, RMS prop (root mean square propagation) optimizer, loss function-binary cross-entropy, and accuracy are used as metrics with a learning rate of 0.001 and executed for 100 epochs with a batch size of 32 and 77.78% classification test accuracy is obtained. An individual test image is also given as input and the filter outputs are obtained.

3.3. Implementation of VGG16

VGG16 is from the visual geometry group, a form of CNN used in many applications for transfer learning. The pre-trained network can be used for other applications as a convolutional base model which can be appended with a new top model of our own, according to our application. Transfer learning generally improves model performance and accuracy. Transfer learning is also applied in medical/dental areas such as tumor detection [18], medical/dental image classifications [13] and many more. Hence in the current study, VGG16 is used to improve accuracy in classifying periodontal cysts images. To implement and build this deep learning model, TensorFlow 2.3.0, Keras 2.4.3, the server of Jupyter notebook 6.4.0 running with Python version 3.8.10, and other data science and machine/deep learning libraries and packages are used from Keras with TensorFlow backend. The VGG16 pre-processing function is used in coding for uniform pre-processing of all input images. The model has a VGG16 pre-trained convolutional base with a top set to false appended by our new top model. The weights of ImageNet are used. The VGG16 with our top model appended is implemented in two ways, the former with a feature extraction approach and the latter with a fine-tuning method. During compilation, RMS prop (root mean square propagation) optimizer, loss function-binary cross-entropy, and accuracy are used as metrics with learning rates of 0.001 and 0.0001 and executed for 100 epochs with a batch size of 32 and 98.48% classification accuracy with both the methods is obtained, thus improving the overall accuracy obtained when compared to CNN. Filter output for an individual image is also obtained.

3.4. Implementation of U-Net

CNN architecture expanded its form for precise segmenting of bio-medical images using U-Net. It is also used in semantic segmentation and object detection. It has a number of dental/medical applications such as dental/medical image segmentation [43], brain image segmentation, teeth segmentation, skin carcinoma segmentation, measuring alveolar bone loss during periodontitis [20] and many more. In the current study, U-Net is implemented in two ways. The first model is a simple implementation of plain U-Net, and, in the second model, the ResNet backbone and ImageNet weights are used. 10 000 RGB panoramic images containing cyst are rescaled to 128×128 using the Image J tool. Before implementing code, a lot of work is done to organize images and their masks in specific folders labeling them to continue with coding. For the first model, images containing cyst and their respective masks obtained from the periodontist are given as input for training. The code is implemented in Google Colab with a Python3 Google compute engine (GPU) using TensorFlow 2.6.0, NumPy 1.19.5, Matplotlib 3.2.2, Keras 2.6.0, h5py 3.1.0 and Python 3.7. Of 10 000 images, 8000 are used for training, 2000 for validation, and 200 for testing, and random checks of a few images are tested to identify cyst area. Masked images are binary images. For both the contraction and expansion path, a 3×3 filter is used, ReLu as activation function and stride of 2×2 with padding. The optimizer used is Adam with loss function binary cross-entropy and accuracy as metrics during compilation. The code is executed for 150 epochs with an 80% – 20% split of training and validation data, and obtains better results when randomly checked on test sample images. The filter outputs are also obtained for a test image. For another implementation of U-Net where ResNet34 and ImageNet are used as the backbone and weights, respectively, in Google Colab segmentation models 1.0.1, TensorFlow 2.1.0, Keras 2.3.1, h5py 2.10.0 are pip installed in Keras framework and TensorFlow backend. 10 000 256×256 sized RGB images and the respective binary masked images are used for training with a 70% – 30% split. The code was compiled with the Adam optimizer, and the Jaccard loss function with IOU (intersection over union) score was used as a metric. The model is executed for 1001 and 1020 epochs. The results obtained are encouraging. It is clearly understood that computers can read images and videos along with normal data, gain high-level understanding, and perform image classification, localization, object detection and semantic/instance segmentation [40]. There are many studies where machine learning, deep learning, the internet of things, big data, fog computing and many types of artificial intelligence have been successfully implemented for medical/dental data sets in the appropriate prediction and analysis of health disorders [21–23]. Thus in this study, deep learning and the associated techniques are implemented on dental images.

4. Results discussion

Periodontitis, when neglected and without proper treatment at the right time, causes severe consequences resulting in tooth loss. In a few cases, the tooth-supporting structures unexpectedly start deteriorating without any symptoms at the initial stages. By the time the patient visits a dentist, there are chances that the deterioration might have already started. Unlike dental caries, this disease cannot be identified by its appearance until some symptoms and signs occur. As it has a significant impact on overall health and past studies proved there is an association between periodontitis and other systemic diseases, the present work focuses on classifying periodontal cyst using deep learning. Also, U-Net architecture is implemented for semantic segmentation of radiographs having a periodontal cyst. The implementation of CNN for training is done with 224×224 sized radiographs, 3905 with cyst and 3917 with no cyst, 996 with cyst and 996 with no cyst 224×224 sized radiographs for validation, and 96 images with cyst and 102 with no cyst for testing. The training is done for 100 epochs with a learning rate of 0.001 and 77.78% testing accuracy is obtained during classification. The outputs obtained when tested on images are represented in Table 1. Also the accuracy and loss plots for 100 epochs are obtained, as shown in Figs. 1a and 1b for the CNN model.

Table 1. CNN output on test images.

Classification	Precision	Recall	F-Score	Support
Cyst	0.728070	0.864583	0.790476	96.0
No cyst	0.845238	0.696078	0.763441	102.0

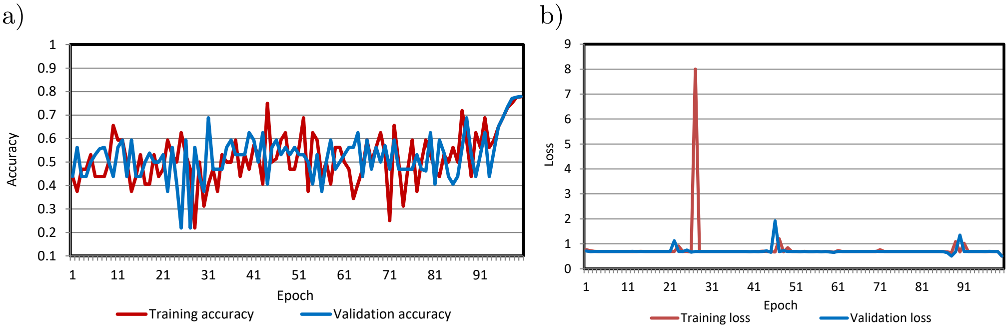

Fig. 1. a) Epoch vs. accuracy plot, and b) epoch vs. loss plot during training by the CNN model.

Figure 2 shows the sample filter outputs of the convolutional layer on a test image obtained by CNN model.

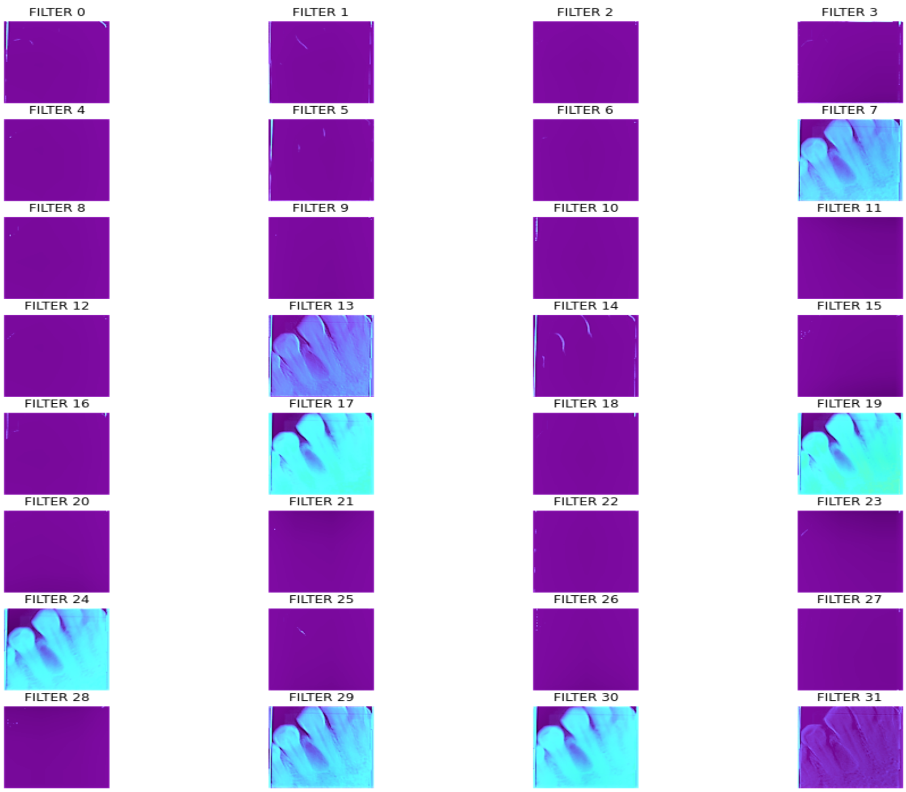

Fig. 2. Filter outputs of the first convolutional layer for a given test image by the CNN model.

As the classification accuracy on test data obtained using CNN is 77.78%, to improve the results, transfer learning through pre-trained VGG16 architecture is incorporated and implemented by creating a new top model on the pre-trained layers. Both feature extraction and fine-tuning methods are implemented and the results are very encouraging. There is a huge improvement in classification accuracy of 98.48% on test data and 100% on training and validation data.

Figures 3a and 3b represent the plots obtained for epoch vs. accuracy and epoch vs. loss during the training phase by the VGG16 feature extraction method. The given diagrams (Figs. 4a and 4b) represent the epoch vs. accuracy and epoch vs. loss plots obtained during the training phase by the VGG16 fine-tuning method.

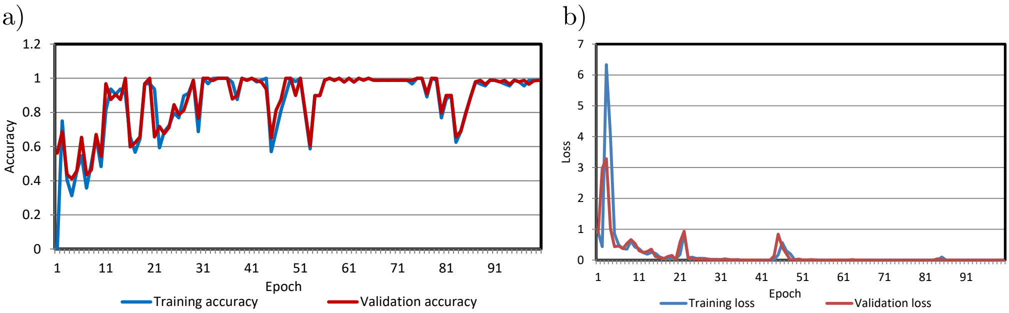

Fig. 3. a) Epoch vs. accuracy plot, and b) epoch vs. loss plot during training by the VGG16 feature extraction method.

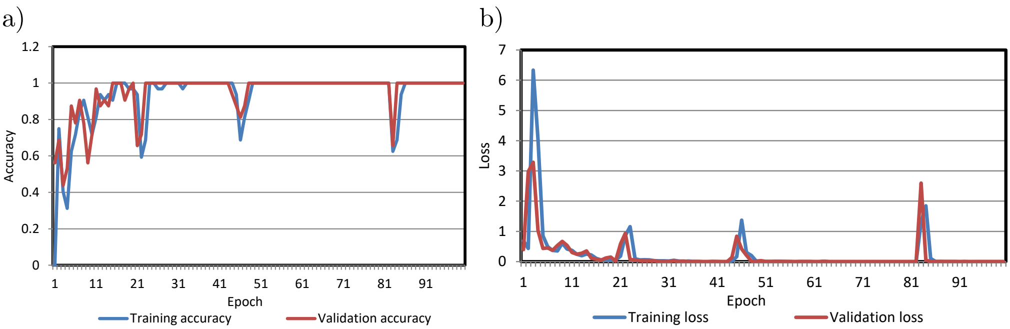

Fig. 4. a) Epoch vs. accuracy plot, and b) epoch vs. loss plot during training by the VGG16 fine-tuning method.

The confusion matrix obtained by both the approaches of VGG16 is displayed in Table 2.

Table 2. Confusion matrix of feature extraction and fine-tuning methods during transfer learning.

	VGG16 – feature extraction			VGG16 – fine-tuning		
True label	Cyst	96	0	Cyst	96	0
	No cyst	3	99	No cyst	3	99
		Cyst	No cyst		Cyst	No cyst
Predicted label						

The filter output of the first convolutional layer on a test image is represented in Fig. 5.

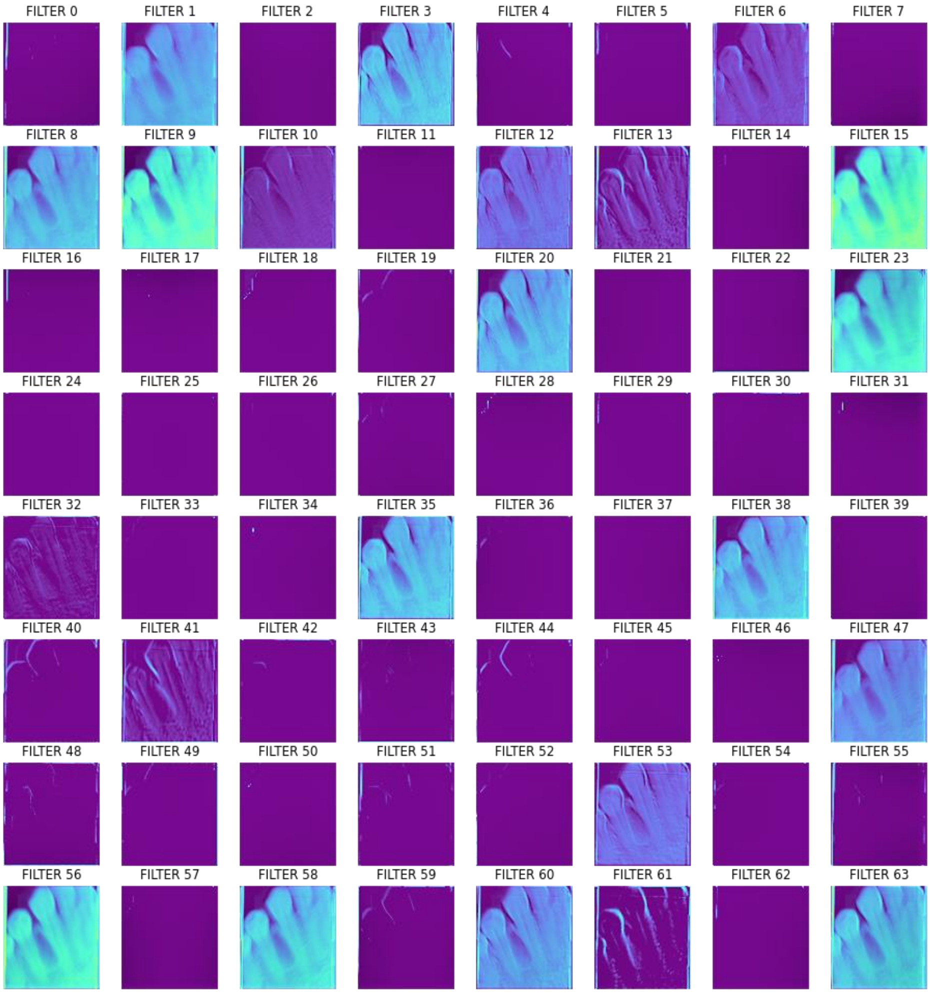

Fig. 5. Filter output of first convolutional layer (64 filter outputs).

From the above results, deep learning models give considerable results for classifying images with a periodontal cyst and without. As with CNN a 77.78% test accuracy is obtained, to improve the results, pre-trained VGG 16 is used, and, by transfer learning, the accuracy is enhanced to 98.48%, thus improving the overall performance. Therefore, deep learning models can be used in periodontics and other dental specializations where early disease prediction, diagnosis and decision-making play a vital role. Further, the present work is not only confined to classification tasks but is also extended to semantic segmentation using U-Net. The first model of U-Net is a simple implementation and in the second model, ImageNet weights and ResNet34 are used as the backbone. The loss and accuracy plots obtained in 150 epochs are presented in Figs. 6a and 6b, taken from the tensor board. The blue line is validation and the orange line represents training. The training and validation accuracies obtained during training are 96.9% and 97.5%, respectively.

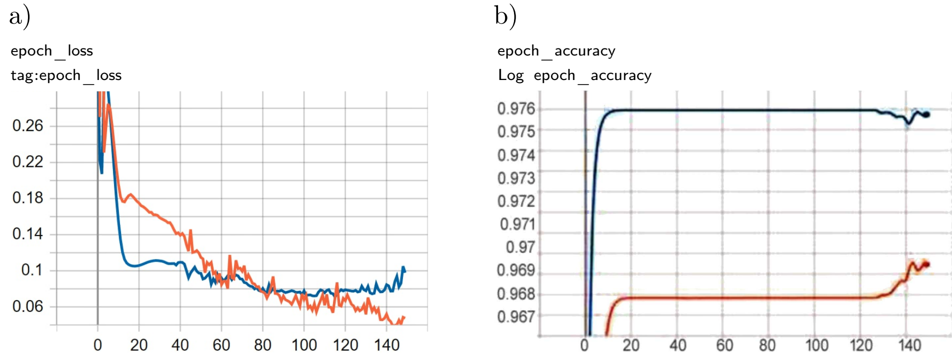

FIG. 6. a) Loss vs. epoch plot, b) accuracy vs. epoch plot.

The outputs obtained by U-Net when sample test images are given to predict the periodontal cyst area are represented in Figs. 7 and 8.

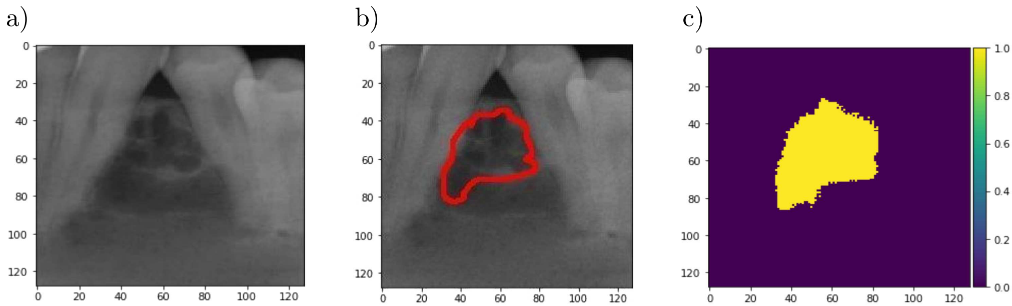

FIG. 7. a) Sample input test images, b) image annotated by a specialist periodontist, c) the predicted output of U-Net on sample input test image.

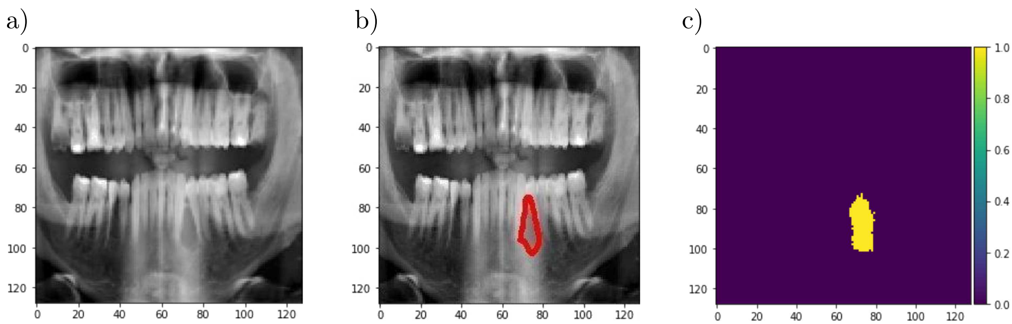

FIG. 8. a) Sample input test images; b) image annotated by a specialist periodontist, c) the predicted output of U-Net on sample input test image.

Figures 7a and 8a present the sample input test images, Figs. 7b and 8b represent the area annotated by a specialist periodontist where the cyst is formed, Figs. 7c and 8c represent the predicted output of U-Net on the sample input test image. The filter output at each convolutional layer is also obtained during execution. The outputs obtained when U-Net is implemented with ResNet34 backbone and ImageNet weights for semantic segmentation are represented in Fig. 9. Figure 9a is the sample test image, and Fig. 9b is the highlighted area containing cyst provided by a specialist periodontist, Fig. 9c is the output obtained by the model for 1001 epochs, Fig. 9d is the output obtained for 1020 epochs. The prediction output obtained also has the area containing cyst, which is the region of interest in the current study.

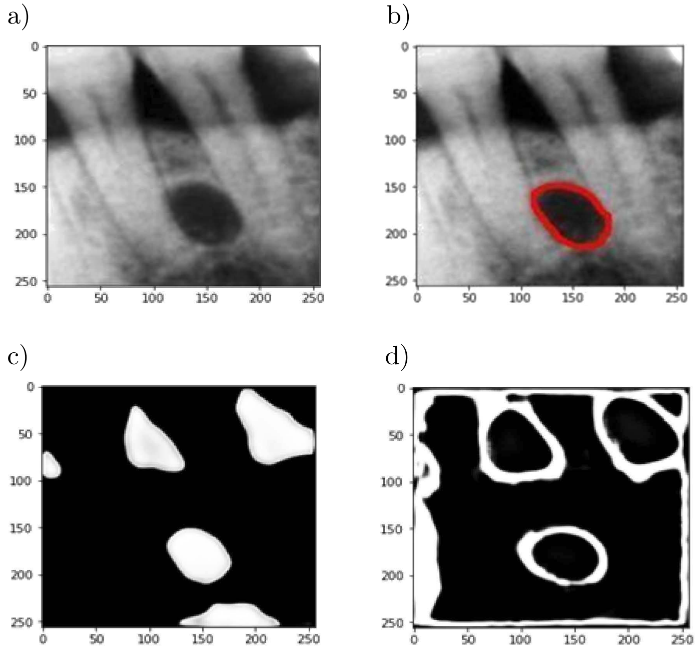

Fig. 9. The sample a) test image, b) the highlighted area containing cyst, c) prediction for 1001 epochs, d) prediction for 1020 epochs.

The execution of voluminous images for such high epochs is a challenging task and takes a lot of GPU time, and this itself becomes a constraint where it has taken nearly 12 hours on Google Colab to complete the execution. Thus in the current study, classification of radiographs for presence and absence of periodontal cyst and segmentation of cyst region is done using deep learning. The limitation of the current work is that the segmentation task on 10 000 images is done for 1001 and 1020 epochs with an execution time of 12 hours, which is tedious and on increasing the epochs, the time to execute still increases more.

Therefore in the future, the work can be extended by finding a novel method to segment the images with an increased number of epochs, reducing the execution time in an alternative way and comparing the results. Also, in the future other segmentation methods can be employed and compared with the proposed method to extract particularly the region of interest where exactly the periodontal cyst is located.

5. Conclusion and future research

Nowadays, many researchers apply machine learning and deep learning, the subsets of artificial intelligence and the world of computer vision, to a wide range of research areas. Decision-making, diagnosis and predictive analysis are the areas where digitalization and use of such advanced technologies are required for effective time-bound and cost-effective treatment planning in medical, dental and allied fields. As oral diseases have a profound impact on overall health, the most burdening oral disease of periodontitis is the focus of the current study. Few oral diseases are identified in the initial stages so that the time-bound treatment planning can avoid further progression of the disease. However, this does not happen in the case of periodontitis. The diagnosis requires regular dental checkups to avoid the rapid progression of the disease. To support the dental practitioner in the effective treatment plan and decision-making during diagnosis, the current study focused on the prediction, classification and segmentation of periodontal cyst. With the deep learning-based CNN for classification, an accuracy of 77.78% was achieved with a 0.001 learning rate for 100 epochs. The classification performance of the model is further enhanced by using the pre-trained VGG16 model, and an improvised performance with an accuracy of 98.48% with 0.001 and 0.0001 learning rates for 100 epochs with both feature extraction and fine-tuning methods is obtained.

In the future, further work can be done in this area as very few research papers focus on this application and instead concentrate mainly on the CNN model to enhance the performance. U-Net was used for the segmentation of images containing cyst areas and achieved fruitful results. Segmentation of images by U-Net at 1001, 1020 epochs is nearly taking 12 hours to execute on Google Colab, which is tedious to follow up the work continuously failing, resulting in the re-execution of the complete work from the beginning. Increasing the number of epochs certainly needs more GPU usage time, and this is the area where a lot of future work can be done to contribute in order to balance the GPU usage time. The work carried out in this paper can be used by future dentists for demonstration purposes and as an aid for decision-making, predictions and analysis. Therefore, in the future the work can be extended to checking with other pre-trained models and weights. Also, there is a lot of scope for further research where the segmentation process can be enhanced to extract the region of interest – the cyst area alone by implementing other imaging techniques and deep learning models.

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