

ENCODER MODIFIED U-NET AND FEATURE PYRAMID NETWORK BASED DETECTION OF DENTAL CARIES USING NIR IMAGES

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Abstract

The technological advancements in machine learning methods have resulted in a growing interest in automated dental caries detection. This is an important issue in dental care, particularly with regards to the detection of caries, as it can lead to serious health problems. To address this issue, this study aims to accurately segment and identify dental diseases. The study proposes a novel technique of segmentation using cascaded U-Net, which is the most widely used network in medical image segmentation. The U-Net architecture, which includes an encoder-decoder structure and skip-connections, can effectively capture multi-scale information in medical images. In the proposed technique, the initial segmentation result of the first stage is used to crop out the region of interest (ROI), which is then fed into the second U-Net. The input image for the second stage retains the original resolution as much as possible to improve segmentation performance. The proposed model is implemented using MATLAB and its performance is compared with existing algorithms in terms of accuracy, F-score, precision, and recall rates.

Introduction

In today's era where there is tremendous change in life of people along with their health habits too. The main problem among children is their tooth problem. There are different tooth problem arising among the children because of their unhealthy eating habits. This is considered as main problem because this defaulting structure of teeth or cavity can cause many problems in the later life of these children. The most common problems among these children are projection of permanent teeth before falling of deciduous teeth either frontward or backward, and another is cavity problems that arises from eating too much of sweet items. This is considered as one the main problem of children and further in this paper the depth between the deciduous teeth and permanent teeth is calculated and, it is also examined where there is cavity present is the teeth.

Dental caries is one of the most common preventable diseases which is recognized as the primary cause of oral pain and tooth loss. It is a major public health oral disease which hinders the achievement and maintenance of oral health in all age groups. WHO pointed that the global problem of oral disease still persists despite great improvements in the oral health of population in several countries. WHO claimed that poor oral health may have a profound effect on general health as well as quality of life, and several oral diseases are related to chronic diseases. food habits and oral hygiene practices. Nowadays, as a consequence of high prevalence of dental caries, the treatment need is increased. However, treatment cost for dental diseases. Machine learning (ML) is the study of computer algorithms that improve automatically through experience. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly

programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or infeasible to develop conventional algorithms to perform the needed tasks.

Machine learning is closely related to computational statistics, which focuses on making predictions using computers. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics. Machine learning involves computers discovering how they can perform tasks without being explicitly programmed to do so. It involves computers learning from data provided so that they carry out certain tasks. For simple tasks assigned to computers, it is possible to program algorithms telling the machine how to execute all steps required to solve the problem at hand; on the computer's part, no learning is needed. For more advanced tasks, it can be challenging for a human to manually create the needed algorithms. In practice, it can turn out to be more effective to help the machine develop its own algorithm, rather than having human programmers specify every needed step.

Ojaghi et al 2016 demonstrate the capabilities of a clinically and commercially viable long-wavelength infrared (LWIR) thermophonic imaging technology in detection of very early proximal and occlusal caries. The system incorporates intensity-modulated light and detects the early caries based on the altered thermal-wave field, caused due to greater light absorption at caries sites, which reaches the IR camera through infrared emission. Liu, Li et al 2018 proposed a simple method based on laser induced fluorescence spectrum with backscattered enhancement for the detection of initial caries on *in vitro* teeth. Fluorescence spectra of carious erosion on different status were given. The radiation of backscattering, reflection and autofluorescence from teeth was registered simultaneously. Devesh et al 2021 aims to detect dental caries using digital color image at an early stage so that the treatment can be performed easily and effectively. Shuai Li; et al proposes a novel network enhanced by a self-attention module for intelligent dental plaque segmentation. The key motivation is to directly utilize oral endoscope images (bypassing the need for dyeing reagent) and get accurate pixel-level dental plaque segmentation results. Dhruv et al 2020 propose a hybrid deep learning and machine learning based approach to detect evident dental caries/periapical infection, altered periodontal bone height, and third molar impactions using panoramic dental radiographs. Pranjit Das et al 2020 proposed a system that aids in lowering morbidity rates and improving the quality of dental care in the population. Using transfer learning techniques, this study aims to automate the detection of dental cavities. The two transfer learning algorithms used are ResNet50 and Mobile Net. Haghanifar et al applied a fuzzy cognitive map (FCMs) to classify patients in terms of their personal risk of dental caries. Two approaches are discussed for developing FCMs. At first, causal relations between concepts and their weights are defined based on the domain experts.

Angelino et al 2018 report construction of a NIR (850 nm) LED imaging system, comprised of a NIR source and an intraoral camera for rapid dental evaluations. The NIR system was used to image teeth of 10 consenting human subjects and successfully detected secondary, amalgam-occluded and

early caries lesions without supplementary image processing. Patil et al 2018 establishes caries diagnosing model. Here, the feature selection is dependent on Multilinear Principal Component Analysis (MPCA). In addition, the classification is performed by exploiting well-known classifier known as Neural Network (NN).

Kumar et al 2019 proposed a method to extract the restoration part from the dental X-ray image by combining the Fuzzy clustering with the iterative level set active contour.

Angelino et al compared clinical features between 2D radiograph, CBCT, and near-infrared transillumination imaging. Found that near-infrared imaging independently, and in some cases exclusively, was successful in identifying early demineralization and shallow enamel features, while radiography was optimal for capturing deeper decay and developed caries. Kaarthik et al offers an exceptional methodology for the programmed distinguishing proof of dental caries. A Multi-Input Deep Convolutional Neural Network Ensemble (MI-DCNNE) model has been used for the proposed procedure. To improve the performance of the suggested MI-DCNNE approach, a score-based ensemble strategy is used. Shih-Lun Chen et al proposal uses artificial intelligence combined with image judgment technology for an improved efficiency on the process. In terms of cropping technology in images, the proposed study uses histogram equalization combined with flat-field correction for pixel value assignment.

Proposed System

In this work, the cascaded U-Net is proposed for dental caries segmentation. The proposed model includes three steps: median filter based preprocessing, cascaded U-Net based segmentation and performance analysis as shown in Figure

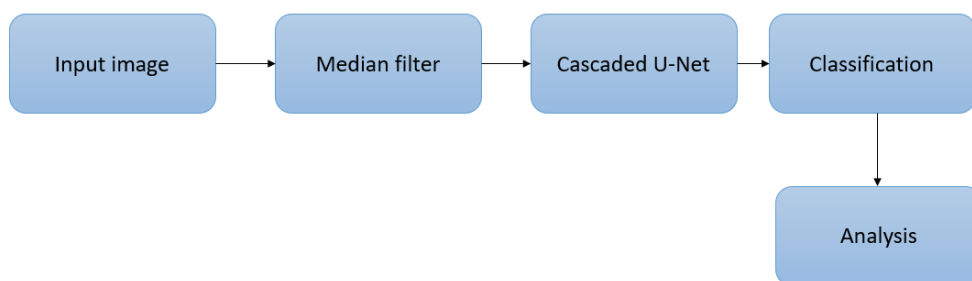


Figure 1 Proposed System

The working steps for cascaded U-Net based dental caries image segmentation with median filtering:

Pre-processing

The first step is to pre-process the dental images by performing median filtering to remove any noise or artifacts that may affect the segmentation process.

Initial Segmentation

In this step, the dental images are fed into the first stage of the cascaded U-Net. The U-Net architecture is designed to effectively capture multi-scale information in medical images, making it suitable for dental image segmentation. The output of this stage is an initial segmentation of the dental image.

Region of Interest (ROI) Extraction

The initial segmentation result is used to crop out the ROI region, which contains the area of interest for dental caries detection.

Feature Extraction

The ROI region is then fed into the second stage of the cascaded U-Net to extract relevant features for dental caries detection. The encoder-decoder structure and skip-connections in the U-Net architecture can capture detailed information from the ROI region, improving the accuracy of the segmentation results.

Post-Processing

The final segmentation result is obtained by performing post-processing techniques such as morphological operations or edge detection to refine the segmentation boundaries.

Evaluation

The segmentation results are evaluated using performance metrics such as accuracy, F-score, precision, and recall rates. The results are compared with existing algorithms to determine the effectiveness of the proposed method. Over all, the proposed methodology of cascaded U-Net based dental caries image segmentation with median filtering involves a series of steps aimed at improving the accuracy of dental caries detection in medical images.

Mean Filtering

Mean filtering is a simple, intuitive and easy to implement a method of smoothing images, *i.e.* reducing the amount of intensity variation between one pixel and the next. It is often used to reduce noise in images. The median filter considers each pixel in the image in turn and looks at its nearby neighbours to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the *mean* of neighbouring pixel values, it replaces it with the *median* of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used).

Segmentation

As can be seen in figure in the first stage, images ($4 \times 128 \times 128 \times 128$) are passed into the first stage U-Net and predict a segmentation map roughly. The coarse segmentation map is fed together with the raw images into the second stage U-net. The second stage can provide a more accurate segmentation map with more network parameters. The two-stage cascaded network is trained in an end-to-end fashion.

For segmentation, we proposed a cascade UNet (see Fig. 1). The data is first resized to a uniform size and fed to the first UNet. The initial segmentation result of the first stage is used to crop out the ROI region and the ROI is fed to the second UNet. The input image for the second stage keeps the original resolution as much as possible, which can improve the segmentation performance. For classification, we take segmentation as an auxiliary task to improve the classification performance.

UNet is the most popular network in medical image segmentation. The encoder-decoder architecture and skip-connection in UNet can capture multi-scale information in medical images. UNet is the preferred network in various medical image segmentation challenges. UNet-I aims to locate nodules and predict the approximate size and shape of nodules. UNet-II aims to refine the prediction results of UNet-I in order to obtain more accurate nodule boundaries. Firstly, all the images are resized to 512×512 to train UNet-I. There is a trade-off between model performance and computing resource consumption for training UNet-II. Larger input size can keep more information at original resolution, but it also needs more GPU memory and time consumption to train the model.

When training UNet-II, the segmentation result of UNet-I will be used as input. We use labels to generate pseudo UNet-I segmentation results. We only hope that UNet-I segmentation results can provide the approximate location and size information of thyroid nodules. It is found through experiments that in the process of training UNet-II, pseudo UNet-I segmentation results should not be too similar to the label, and UNet-II will take a shortcut and copy UNet-I results directly to the output instead of learning how to recognize the original image. Therefore, ellipse fitting, geometric transformation and cutout are used to erase the detailed information in UNet-I results. Geometric transformation includes small scale, translation and 180° random rotation.

Results and Discussion

Confusion Matrix as the name suggests gives us a matrix as output and describes the complete performance of the model.

n=165	Predicted:	Predicted:
	NO	YES
Actual:		
NO	50	10
Actual:		
YES	5	100

Confusion Matrix

There are 4 important terms:

True Positives: The cases in which we predicted YES and the actual output was also YES.

- **True Negatives:** The cases in which we predicted NO and the actual output was NO.
- **False Positives:** The cases in which we predicted YES and the actual output was NO.
- **False Negatives:** The cases in which we predicted NO and the actual output was YES.

Accuracy for the matrix can be calculated by taking average of the values lying across the “**main diagonal**” i.e

$$Accuracy = \frac{TruePositive + TrueNegative}{TotalSample}$$

$$\therefore Accuracy = \frac{100 + 50}{165} = 0.91$$

Confusion Matrix forms the basis for the other types of metrics.

The proposed model is compared to other models in terms of Accuracy, Specificity, Recall and Precision rate measurements. These measurements can be defined as:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (6)$$

$$Specificity = (TN) / (TN + FP) \quad (7)$$

$$Recall = (TP) / (TP + FN) \quad (8)$$

$$Precision = TP / (TP + FP) \quad (9)$$

where FP is the false positive, FN is the false negative, TP is the true positive and TN is the true negative of the samples.

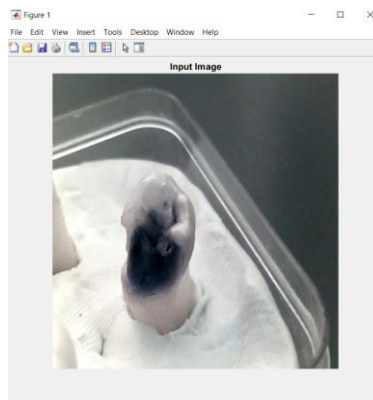


Figure 2 Input Image

The above figure shows the input image for classification

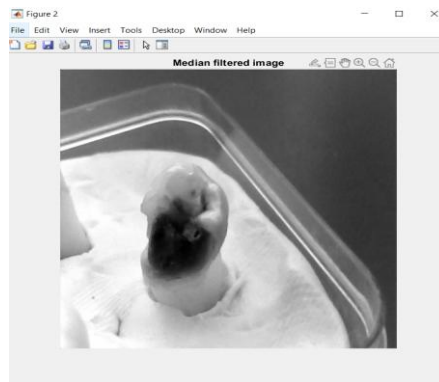


Figure 3 Median Filtered Image

The above figure shows the median filtered output image for further processing

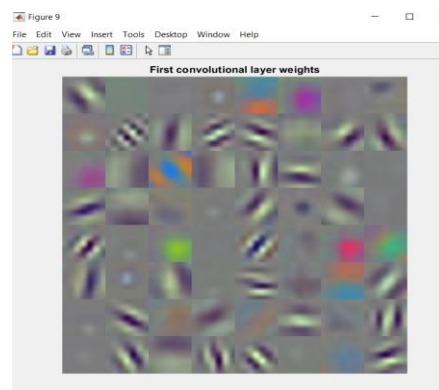


Figure 4 Layer Calculation of U-Net

The above figure shows the layer mapping of proposed cascaded U-Net

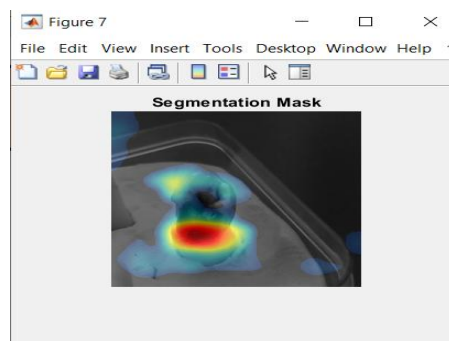


Figure 5 Segmentation Output

The above figure shows the segmentation results of proposed model

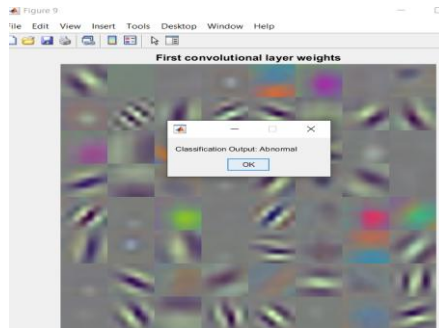


Figure 6 Classification Output

The above figure shows the classification output

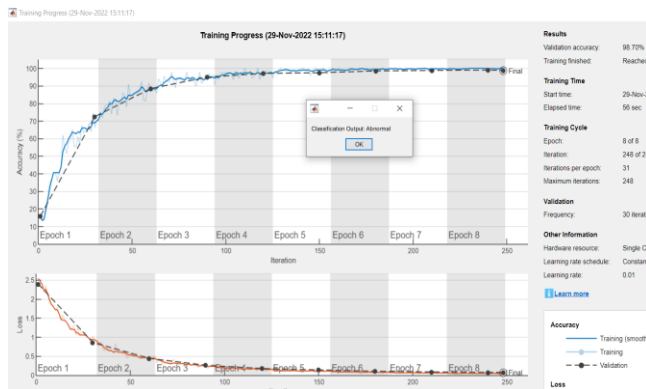


Figure 7 Validation Output

```

17 - disp(['Selected File Name: ', int_image])
18 - delete '/TestData/*.*');

Command Window
New to MATLAB? See resources for Getting Started.
Pnsr
40.4207

Predicted Label: abnormal

TPR= 0.00904052|
FPR= 0.00218438
accuracy= 0.972245
precision= 0.492174
    
```

Figure 8 Performance Analysis

Conclusion

A new approach for identifying cavities in dental images is presented in this research. The proposed methodology involves traditional image processing techniques, including segmentation,

image enhancement, and contour illustration of teeth to complete the segmentation process. In addition, the research utilizes cascaded U-Net to extract relevant features from dental images. These extracted features can be used to obtain measurements of teeth for dental diagnosis systems. The main objective of this approach is to achieve efficient classification or diagnosis of dental caries based on the images. The results obtained from this study demonstrate a high level of accuracy in detecting cavities using the proposed technique.

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