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Deep Learning Approach for Partitioning of Teeth in Panoramic Dental X-Ray Images

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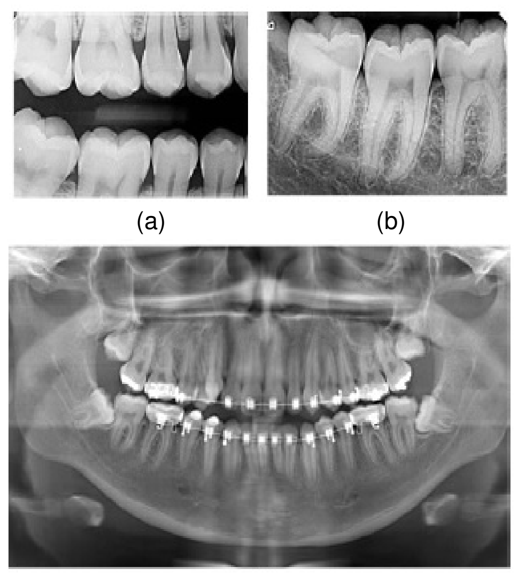
ABSTRACT: Panoramic dental X-ray is widely used in many medical fields. Panoramic dental X-ray helps to extract the entire mouth in single image. The extracted image used by dentist and surgeons to plan for the treatment for implants, dentures etc. For the accurate prediction of treatment. In this proposed methodology, deep learning approach is performed. The extracted image of panoramic dental X-ray cannot be directly used for diagnosis. The captured image contains disturbances like noise, blurred image etc. To get a high quality image from extracted panoramic dental X-ray. This approach is performed. To the extracted images, partitioning is performed to split up the images into samples. It helps for better recognition and classification. It shows the infected region of the teeth accurately. Before performing partitioning, the extracted image has to be preprocessed to clear out the disturbances in the image. After partitioning, feature extraction is performed by using GLCM and finally classification is performed between the trained and test set data to produce a high accurate image. It is done by using CNN classifier. This processed image helps the dentist for good prediction.

Keywords: panoramic dental X-ray, Notch Filter, Graylevel co-occurrence matrix (GLCM), Convolutional neural network classifier (CNN).

I. INTRODUCTION

Dentistry has witnessed tremendous advances in all its medical field. With these advances, there is a need for more precise diagnostic tool. Panoramic dental x-ray have also found place in modern dentistry. In this work, panoramic dental x-ray was used to extract the entire mouth in single image. It made the complex work more accessible for examination. This paper is to review the trending advances in imaging technology and their uses in different disciplines of dentistry. For the precise prediction, deep learning approach is used in the panoramic dental x-ray image for partitioning the teeth and to get a high quality image. Several approaches were used in the existing work but this proposed work outperforms well compared to other work.

Wu *et al*., (2018) discussed about the model based orthodontic assessment in the panoramic radiographs. In this work, they have used a set of parameters to obtain a reliable information for the best treatment plan. The used parameters are Reliable Crown Vertical Position (RVCP), Absolute Crown Vertical Position (ACVP), Axis angulation (AANG) and Crown overlapping area (COA). The ACVP and COA are new parameters that consumes more time and difficult to find [1]. Gan *et al*., (2017) [4] they have discussed about the tooth and alveolar bone segmentation from CT images. They used tooth contour propagation strategy for performing segmentation. By using this strategy, it suffers from serious accumulated error problem. Mao *et al*., (2018) [8] they have presented in detail about the Grab cut algorithm which is used for segmenting the dental X-ray image. Even though this algorithm is very fast and easy to implement. The drawback of this proposed work is, the result becomes unstable.



(a) (b)

(c)

Fig. 1. Illustrates the image extraction of X-rays tumor after the automatic detection.

To overcome this drawback. In this proposed methodology, deep learning approach is performed in the panoramic dental X-ray image. Panoramic dental X-ray is chosen because it ionizes less radiation. It shows the image in a two dimensional view. This panoramic dental X-ray tries to project the teeth arch in orthogonal view. To the extracted panoramic image, deep learning approach is utilized to achieve high accuracy.

II. MATERIALS AND METHODS

A. Literature Survey

Jo *et al*., (2017) proposed a tileable CMOS X-ray line detector using time-delay-integration with pseudo multisampling for large-sized dental X-ray imaging systems. In this paper, to make available a bigger dental X-ray imaging system with reduced noise and power consumption, a tileable CMOS X-ray line detector has been proposed. Based on the photolithographic area, the peripheral circuit and has 252 column readout circuit each in the four banks present, are locate. The noise reduction result remains as same as that of the traditional system when nPMS is less than Σi N [2].

Lira *et al*., (2014) proposed a dental X-ray picture division by utilizing texture recognition. In this paper, to overcome the problems of previously installed system, a new procedure to encourage the dentist on doing his procedures, a radiographic image which captures the segmentation in the teeth has been proposed. For attaining the texture recognition in an extreme precision, the technique which helps in various medical fields named as supervised technique is employed. However, positioning of the holder in the mouth is difficult, the patient may feel uncomfortable too [7].

Guo *et al*., (2017) proposed a deep learning-based image segmentation on multimodal medical imaging. In this paper, for multimodal processing of the image, a design methodology is needed, for the development of which an architecture that can provide image fusion strategies has been proposed. The image segmentation technique employed for the multi-modal appears to work individually, because of which it can be utilized a general design for various types of issues. It is concluded that the extra modality is not suitable for the segmentation task, if it exhibits a performance drop [13].

Enguehard *et al*., (2019) proposed a semi-supervised study with deep embedded grouping for image classification and segmentation. In this paper, to resolve the issues of labeling the data with low time consumption and also reducing the cost while performing medical image segmentation, a semi-supervised technique has been proposed. An improvement in the performance of supervised-only technique is obtained, by integrating the proposed semi-supervised algorithm, with limited number of labeled training samples. Even though the clustering algorithm enables the production of clusters directly from the data, because of the dimensionality some issues arrives [18].

Dai *et al*., (2018) proposed a clinical report guided retinal micro aneurysm detection with multi-sieving deep learning. In this paper, to work together with the detection issue of an unbalanced micro aneurysm, a deep mining technique has been proposed. For identifying the feature combination, various subspaces are obtained from the feature spaces; each of the subspaces contains different combinations of feature. Low preciseness and recall tends to appear in the system which showed up due to the difficulty in identifying the small objects, when the semantic segmentation method is directly applied to our case [19].

III. PROPOSED SYSTEM

The image of panoramic X-ray is the 2D perspective of the teeth. The image which is extracted by panoramic X-ray is the variation of patient to patient teeth, uniformity in areas close to the object, gap between the existences of missing tooth. Segmentation is performed in parts of the image retrieved from the panoramic X-ray it helps the specialist to diagnose the problem occurred in the teeth. Some issues identified in panoramic X-ray pictures are shown in Fig. 2.

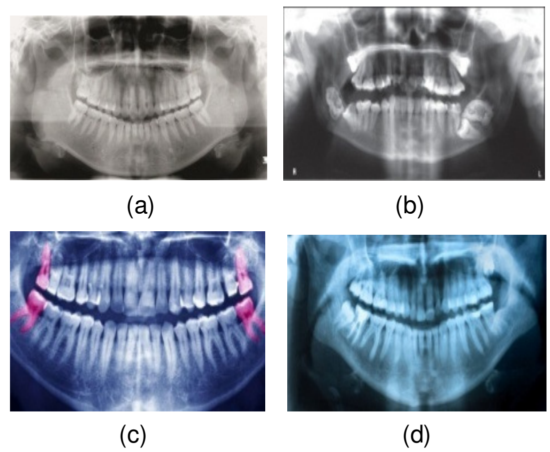


Fig. 2. Sample problems of panoramic X-ray pictures: (a) Dental implantation, restored teeth view of some teeth; (b) supernumerary teeth; (c) devices for mandibular trauma; (d) missing and detached teeth.

The input image cannot be directly processed as it is ineffective and impractical in image recognition and compression for disease analysis. Image division is a process of clustering or classifying the picture into many parts regarding the image features for analysing the image. It can annotate the data and recognize the regions of interest in medical image processing applications. The existing chapter issues are overcome by this proposed work. GLCM Segments analysis is a process usually associated feature extraction for image classification. Analysis of segment is a process is utilized to mark the segments of CNN classifier.

Pruning an initial set of features from ineffective subsets of features to give a smaller effective set is called feature selection. Most of the techniques for feature selection are based on statistical distance measures. The correlation based feature selection increase the accuracy of the classification.

The input image is given to the pre-processing state in order to reduce the noise and crop the test data image from the input image. Then cropped image is converted into samples, it is achieved using segmentation process. The GLCM is used to extract the samples amplitude. The correlation based feature selection generates the trained data set. Both these features are compared using CNN classifier.

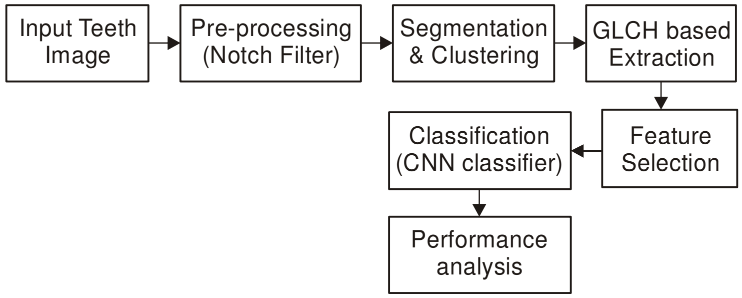


Fig. 3. Proposed system block diagram using CNN classifier.

Pre-processing: Generally notch filter is named as band rejection or band stop filter. Notch filters are proposed to transmit data with less power misfortune while lessening data inside a particular wavelength range (the stop band) to a low level.

Data Clustering: Clustering is the route toward isolating information which focuses into image samples or clusters with the objective that the things in a similar class are comparable and things in various classes are disparate. In view of the possibility of the data and the explanation behind which clustering is being used, particular measures of closeness may be utilized to place things into classes, where the likeness measure controls how the gatherings are surrounded. A couple of instances of measures that can be used as in gathering join separation of the image. In hard clustering, data are apportioned into specific gatherings, where each data segment has a place with precisely one group from the teeth images. In fuzzy clustering, data parts can have a place with more than one gathering, which is more, accompanied with each segment is a course of action of membership levels. This exhibit the idea of the connection between that information part and a specific gathering of fuzzy clustering is an arrangement of propelling these enrolment levels, and subsequently utilizing them to apportion information parts to at least one get together. A champion among the most comprehensively used Fuzzy gathering tallies is the Fuzzy C-Means (FCM) Algorithm is used to form cluster in the detection image.

This emphasis relies upon constraining participation work that addresses the detachment from any given data point. The fuzzy is an approach to prepare the information by giving the halfway participation incentive to every pixel in the picture. The enrolment estimation of the fuzzy set is ranged from 0 to 1 from the membership function. FCM is multi esteemed bunching where the participation of every fuzzy set will be varied from another fuzzy set from the input images. A prior specification is given to the number of clusters and it is a time consuming algorithm because number of iteration required is more. It is a time consuming algorithm and degrades the accuracy and sensitivity of the system. There is no sudden move between full enrolment and nonparticipation. The participation work describes the fuzziness of a picture and moreover portrays the information contained in the input image.

In statistic and segmentation data clustering is widely used for medical image processing applications. In the significant concept of clustering of data is to represent all the centroid is used and the centroid of cluster is based on the similarity to classify. Hence it is divided into "hierarchical clustering" and "Partition clustering" regarding the above characteristics.

Hierarchical Clustering: Hierarchical Clustering is used to implement a dendogram (shows hierarchical relation between objects) with grouping of patterns in nested form and to change groupings in combination with similar levels of the input teeth images. In hierarchical clustering, the number of clusters need not be specified in prior where only local neighbours in each step are considered. To interpret the hierarchical clustering algorithm function two dimensional data set is applied. The hierarchical clustering is subdivided into two categories, namely, the hierarchical agglomerative algorithm and hierarchical divisive algorithm.

Hierarchical agglomerative method is stated below:

Step 1: In the database each pattern is set as a cluster Ci and distance in between all pair of patterns is computed with proximity matrix.

Step 2: The common alike pair of clusters is found by using proximity matrix and the two clusters are merged into single cluster. Finally, modify the proximity matrix.

Step 3: Repeat Step 1 and 2 until all patterns in one cluster achieve the resemblance.

The each pair of sample distance is noticed in several ways from the input image. The single-link algorithm and complete-link algorithm are the most popular definitions. If D (Ci, Cj) is assumed as the distance in between cluster Ci and Cj, and the distance between pattern a and b assumed as d (a, b) as.

$$D(C_i, C_j) = \min(d(a,b)), \quad f\text{or}\forall a \in C_i, \forall b \in C_j, \qquad (1)$$

The distance between two groups is the smallest of all pair wise distances i between two clusters in every one of the examples. The definition for separation of finish connect strategy is expressed beneath

$$D(C_i, C_j) = \max(d(a,b)), f \text{ or } \forall a \in C_i, \forall b \in C_j, \qquad (2)$$

Equation (2) implies the most extreme of the distances between all sets of examples in the two clusters is the separation between two clusters. Clusters created by this are more than single link strategy is the geniuses of finish interface technique. Also, the complete link technique, isn't as adaptable as the single link strategy, in numerous applications the entire connection strategy creates more handy progressive systems than the single-link technique.

Feature Extraction: Features are unique properties of information that help in separating the information patterns in the classification phase from the image. Features may be crude pixels for basic issues. Utilization of basic image pixels is not sufficiently clear.

Changing the information on behalf of the arrangement of features is called Feature Extraction. Feature Extraction is typically distinguished as diminished list of capabilities to speak to the errand. The portions of the components are colour histogram, zone and so on in the image. They are utilized for perceiving shapes and for the most part utilized as global feature. Some different sorts of features are texture, intensity and so forth. These elements tell about spatial introduction and its degree. These features are called as local feature. It is important to recognize when to utilize global feature and local feature. By considering the portrayal of the significant functions the separated feature ought to give the attributes of the info to the classifier. Typically Extracted features are

— Shape Features

Shape Index

— Intensity features

Median Intensity, Mean, Variance, Standard Variance

— Texture features

Contrast, Interconnection, Entropy, Energy, Homogeneity, sum of square variance

These three sorts of features portray the structure data of intensity, shape, and texture. In the following stage the feature selection is performed to lessen the repetition.

Gray Level Co-Occurrence Matrix (GLCM): A notable procedure to extricate feature is to utilize Gray Level Co-event Matrices (GLCMs), which have a place with measurable technique in teeth analysis. The GLCM contain the second-arrange measurable data of spatial association the pixels of an image. The GLCM comprise data almost in what way frequently a pixel with grey level value i happens either vertically, on a horizontally, or diagonal to the neighbouring pixels with the value j, where i and j are the dark level values introduced in an input teeth image.

Energy is a component that measures the smoothness of the input picture. Correlation is a grey tone measure of direct conditions in picture. The parameter Homogeneity, otherwise called 'inverse difference moment' measures picture homogeneity as it accepts bigger esteems for littler grey tone contrasts in combine components. Contrast for a bordering set of pixels, is a measure of contrast between the most astounding and the least esteems in it. Hence GLCM using feature extraction is implements the potential component vectors for more image based disease diagnosis. In general GLCM deals with features of the image to be segmented. In our work we are working with problem area segmentation. By this operation, feature calculation will be pointed in particular region only so that output will be better than existing approach.

GLCM is a procedure broadly used to extract features. It is a critical technique for extracting highlights by registering the pixel pair relationship in the picture. The co-event grid C(I, j) is the number the pixels co-event with grey qualities I and j. The co-event framework measurement is N*N. From now on, the multifaceted nature in calculation relies upon the check of dark scales used for quantization. Various components like vitality, relationship, dormancy and entropy are removed from co-event grid to limit feature set dimensionality.

$$\text{Inertia} = \sum_i \sum_j (i-j)^2 \, c(i,j) \quad (3)$$

Variance and contrast is also defined as inertia. In GLCM, the local variations are measured.

$$\text{Correlation} = \frac{\sum_i \sum_j (i-\mu_i)(j-\mu_j) c(i,j)}{\sigma_i \sigma_j} \quad (4)$$

Occurrences of joint probability of the specified pixel pairs are measured.

$$\text{Energy} = \sum_i \sum_j c(i,j)^2 \quad (5)$$

Squared elements sum is provided by energy in gray level co-occurrence matrix.

$$\text{Homogeneity} = \sum_{i,j} \frac{c(i,j)}{1+|i-j|} \quad (6)$$

Distribution components closeness is estimated by homogeneity in grey level co-event array to grey level co-event matrix diagonal. Clustering is used apart from using direct feature extraction. These clusters are formed with regards to segmentation. By this, RoI is predicted. Thus it makes easy to calculate the features.

CNN Classifier: In image processing CNNs was initially utilized applications that are specific sort of NNs. In AI propelled science arguably CNN are the best models. The core design principles were drawn from neuroscience despite the fact that they were guided by a wide range of fields. They were effectively deployed in video processing and natural language applications since they are fruitful in image processing. Neurophysiologists named Hubel and Wisel, explored vision system of warm blooded creatures from late 1950 for quite a long while. In the trial, they considered minimal grim for the present benchmarks, they connected anodes into mind of anesthetized feline and estimated cerebrum reaction to visual stimuli. It is found that response of neurons in visual cortex was activated by extremely slender line of light sparkled under particular point on projection screen for visual cortex to see. Just to bring unmistakable examples in input picture they discover that individual neurons from visual cortex are responding. In 1981 for their revelation Hubel and Wiesel were granted the Nobel Prize in Physiology and Medicine.

Convolutional Layer of CNN Classifier: Convolutional layers are neural system layers saving the spatial structure, which is the essential distinction from customary completely associated neural system layers. Having, for instance, 32 × 32 × 3 picture, rather than extending it to the one-dimensional vector of 3072 things, the picture is kept in its unique 2D structure. By applying the convolutional channel, the information is changed into an alternate tensor called actuation map that additionally protects basic properties. Since enactment maps can be convolved again without loss of auxiliary data, stacked convolutional layers can be utilized for dimensionality decrease of spatial information into low-dimensional element rich vector space where regular completely associated systems can be applied. The channels are little grids of numbers that are increased by districts of information. For each pixel in the info layer, the focal point of the channel is adjusted to it and channel is increased with the area of contribution of a similar size as the channel. This procedure is rehashed for all pixels aside from those not having an adequately enormous neighborhood, bringing about initiation guide of somewhat littler size.

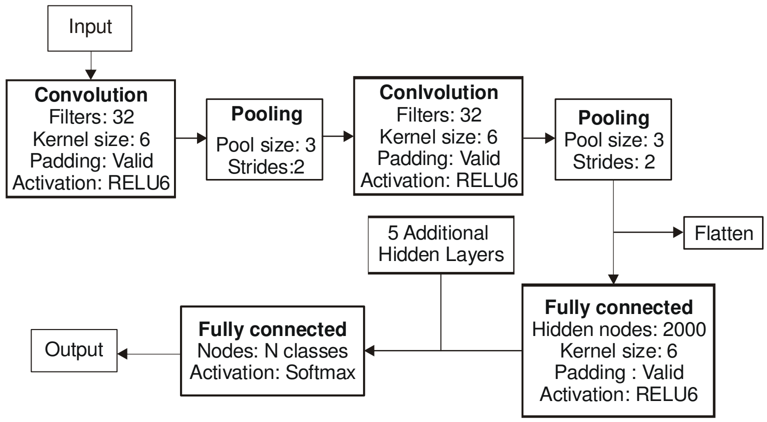


Fig. 4. CNN classifier flow diagram.

Redundancy of applying the channel over the picture can be seen as a channel sliding over the picture, henceforth convolution. A channel consistently expands the first profundity of info.

Pooling Layer of CNN Classifier: An elective way to deal with contract input volume region is to utilize a pooling layer. Pooling layer performs collections over areas rather than duplication with channels of prepared loads. Typically performed conglomeration is limit of the area, giving the name of the maximum pooling layer. The instinct behind successfully of max-pooling layer in grouping task is that it doesn't make a difference where in the locale have include been found as long as it has been found. Taking the limit of an area of actuations dismisses immaterial pieces of that district and reports nearness of the element in the entire locale. On the off chance that averaging were to be utilized rather than most extreme, the way that element was not recognized in rest of the area would negatively affect noteworthy initiations. Pooling layer has no trainable parameters. Most normal use of pooling layer is down-inspecting; thusly walk is set up so districts are not covering.

A solitary channel is searching for a specific component in the information. There are numerous highlights to be found in a picture. In this manner numerous channels are required. Thinking about the utilization of numerous channels, each channel brings about its own enactment map, together yielding a heap of initiation maps called yield volume. Along these lines, an info picture can be changed into a lot further volume (remember the distinction between the profundity of volume meaning a third measurement and profundity of neural system as various layers). Instinctively, as info is being changed from input picture towards highlights over the system, the territory of information volumes is diminishing with applied walk as well as pooling, while the profundity of info volumes can both increment and reduction dependent on the quantity of utilized channels in convolutions. To condense, single convolutional layer requires four hyper parameters: number of channels, channel size, walk and measure of zero cushioning.

In feed forward the data is fed into the model and output from each layer is obtained, we the error is calculated using an error function, some common error functions are cross entropy, square loss error etc. Finally the model is back propagated by calculating the derivatives. This step is called back propagation which basically is used to minimize the loss.

Structure of CNN: Convolutional systems Structure is normally made out of three kinds of layers. Layer can be either Convolutional, Pooling or completely associated. For forward and error backward signal propagation in each sort of layer has distinctive tenets. There are no exact standards on how the structure of individual layers ought to be composed. Anyway with special case of late advancement CNNs are normally organized in two sections. Initial segment called feature extraction, is utilizing mixes of convolutional and pooling layers. Second part called classification in utilizing completely associated layers.

Training of CNN: Enhancement procedure of CNN is analogous to FCNN. Network is made out of various kinds of layers as a result of that circumstance with CNN is more complicated. Forward signal propagation and backward error propagation are following uncommon rules for each layer. Equations utilized as a part of this area were motivated from. First stage is called forward-propagation, where the signal is propagated from contributions of the CNNs to its output. The output is contrasted and wanted an incentive by cost capacity and error is evaluated in the last layer.

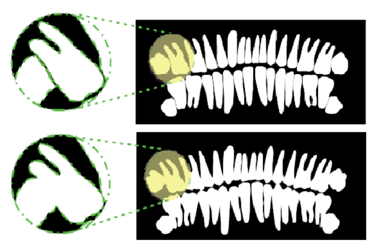


Fig. 5. Process of separating the teeth in the acquired data.

Back propagation algorithm again used as a part of second stage to appraise blunder commitment for singular units. Variable parameters of the system are again streamlining by gradient descent algorithm.

IV. RESULTS AND DISCUSSION

A cohort of 80 images were taken for analysis and it was modified by partitioning the teeth into 256 samples. In order to train the image, partitioning of teeth in each image was done for better performance. To be more effective, 80 image data set is taken. 50 images were used for training and the remaining 30 images were used for performing deep learning approach. Finally both trained and test set data were taken for comparison. By analogizing, it generates the high accuracy.

Quantitative analysis: To evaluate the performance, the following metrics were used:

$\text{Accuracy} = (TP + TN)\,(TP + FN + FP + TN)$,

$\text{Specificity} = TN\,(TN + FP)$

$\text{Precision} = TP\,(TP + FP)$,

$\text{Recall} = TP\,(TP + FN)$, and

$F1 - \text{score} = 2\ \text{Recall Precision}\ (\text{Recall} + \text{Precision})$,

where TP represents true positive

TN indicates true negative

FN indicates false negative and FP stands for false positive. These metrics were used in pixel-wise.

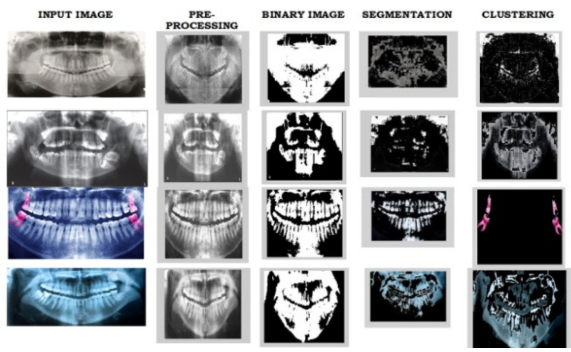


Fig. 6. Proposed System results using CNN classifier with data set 1.

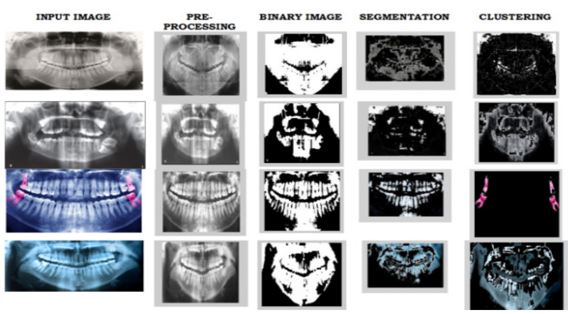


Fig. 7. Proposed System results using CNN classifier with data set 2.

Qualitative analysis: Fig. 7 shows the best result and worst result is shown in each metric in Fig. 7. From left to right, original image, ground tooth, segmentation and image segmentation in each image is shown in Fig. 7. The good result is generated in best partitioning of image. In best partitioning, accuracy, specificity and precision generates the good output except f1 and recall.

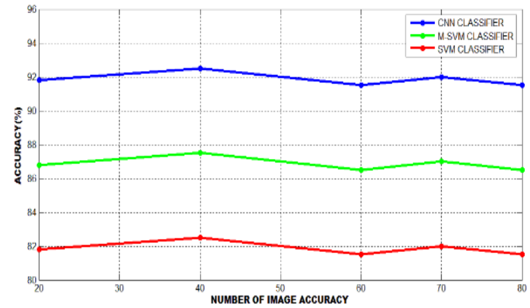


Fig. 8. Accuracy Comparison graph.

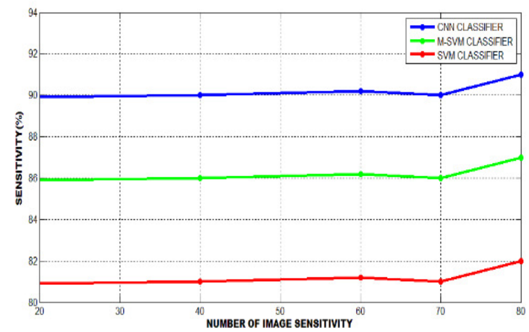


Fig. 9. Sensitivity Comparison graph.

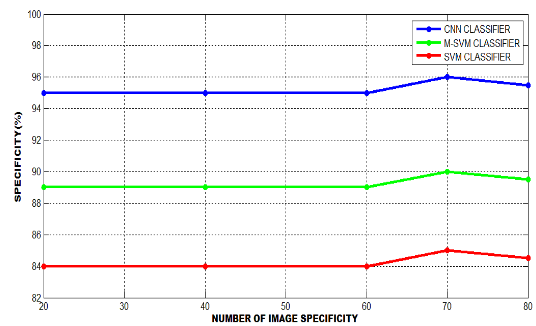


Fig. 10. Specificity Comparison graph.

In worst performance of image partitioning, even specificity and accuracy is high others produces a worst output. The table shows the deviation between CBCT image and panoramic dental X-ray image. By using panoramic dental X-ray image in this proposed work, it achieves high accuracy and precision. The streamlining to decrease the hunt dimensionality would not expand the calculation extend and also the execution of the proposed framework is well-improved with respect to order exactness, accuracy and f-score esteems. Time parameter is undermined with division and arrangement exactness.

Table 1: Accuracy and precision comparison.

Image No.	Accuracy		Precision	
	With CBCT Imaging	With Panoramic Imaging	With CBCT Imaging	With Panoramic Imaging
Image 1	88.6	91.3	87.32	92.6
Image 2	87.3	92.4	86.43	93.6
Image 3	89.4	92.6	88.2	94.8
Image 4	88.9	92.1	89.3	95.1
Image 5	89.3	94.23	88.67	94.87

Table 2: F-Score and computation time comparison.

Image No.	F- Score		Computation Time(ns)	
	With CBCT Imaging	With Panoramic Imaging	With Panoramic Imaging	With CBCT Imaging
Image 1	89.4	90.6	0.72	0.81
Image 2	87.65	91.2	0.74	0.83
Image 3	88.34	93.2	0.78	0.84
Image 4	86.43	94.6	0.82	0.832
Image 5	89.32	93.34	0.75	0.861

V. CONCLUSION

Deep learning technique is used for Partitioning the teeth in panoramic dental X-ray are proposed in this paper. Panoramic X-ray image is used for the visual examination of teeth. It provides the reliable radiographic report compared to other X-Ray reports. Several techniques were used in previous work, but the expected result was not generated. In this paper, Convolutional Neural Network technique was implemented in partitioning the image. It is chosen for partition because of its high accuracy. The high accuracy is needed for the dentist to diagnose the problem and to plan for the treatment accordingly. Compared to other works, it takes less consumption of time and high accuracy is generated.

REFERENCES

[1]. Wu, C. H., Tsai, W. H., Chen, Y. H., Liu, J. K., & Sun, Y. N. (2018). Model-based orthodontic assessments for dental panoramic radiographs. *IEEE journal of biomedical and health informatics*, *22*(2), 545-551.

[2]. Jo, Y. R., Hong, S. K., & Kwon, O. K. (2016). A tileable CMOS X-ray line detector using time-delay-integration with pseudomultisampling for large-sized dental X-ray imaging systems. *IEEE Transactions on Electron Devices*, *64*(1), 211-216.

[3]. Oktay, A. B. (2017). Human identification with dental panoramic radiographic images. *IET Biometrics*, *7*(4), 349-355.

[4]. Gan, Y., Xia, Z., Xiong, J., Li, G., & Zhao, Q. (2017). Tooth and alveolar bone segmentation from dental computed tomography images. *IEEE journal of biomedical and health informatics*, *22*(1), 196-204.

[5]. Lashgari, M., Shahmoradi, M., Rabbani, H., & Swain, M. (2018). Missing Surface Estimation Based on Modified Tikhonov Regularization: Application for Destructed Dental Tissue. *IEEE Transactions on Image Processing*, *27*(5), 2433-2446.

[6]. Hatvani, J., Horváth, A., Michetti, J., Basarab, A., Kouamé, D., & Gyöngy, M. (2018). Deep learning-based super-resolution applied to dental computed tomography. *IEEE Transactions on Radiation and Plasma Medical Sciences*, *3*(2), 120-128.

[7]. Lira, P. H. M., Giraldi, G. A., Neves, L. A. P., & Feijoo, R. A. (2014). Dental r-ray image segmentation using texture recognition. *IEEE Latin America Transactions*, *12*(4), 694-698.

[8]. Mao, J., Wang, K., Hu, Y., Sheng, W., & Feng, Q. (2018). GrabCut algorithm for dental X-ray images based on full threshold segmentation. *IET Image Processing*, *12*(12), 2330-2335.

[9]. Xu, X., Liu, C., & Zheng, Y. (2018). 3D tooth segmentation and labeling using deep convolutional neural networks. *IEEE transactions on visualization and computer graphics*, *25*(7), 2336-2348.

[10]. Li, R., Zeng, T., Peng, H., & Ji, S. (2017). Deep learning segmentation of optical microscopy images improves 3-D neuron reconstruction. *IEEE transactions on medical imaging*, *36*(7), 1533-1541.

[11]. Li, Q., Feng, B., Xie, L., Liang, P., Zhang, H., & Wang, T. (2015). A cross-modality learning approach for vessel segmentation in retinal images. *IEEE transactions on medical imaging*, *35*(1), 109-118.

[12]. Soomro, T. A., Afifi, A. J., Zheng, L., Soomro, S., Gao, J., Hellwich, O., & Paul, M. (2019). Deep Learning Models for Retinal Blood Vessels Segmentation: A Review. *IEEE Access*, *7*(6), 71696-71717.

[13]. Guo, Z., Li, X., Huang, H., Guo, N., & Li, Q. (2019). Deep Learning-Based Image Segmentation on Multimodal Medical Imaging. *IEEE Transactions on Radiation and Plasma Medical Sciences*, *3*(2), 162-169.

[14]. Jia, Z., Huang, X., Eric, I., Chang, C., & Xu, Y. (2017). Constrained deep weak supervision for histopathology image segmentation. *IEEE transactions on medical imaging*, *36*(11), 2376-2388.

[15]. Xia, Z., Gan, Y., Xiong, J., Zhao, Q., & Chen, J. (2016). Crown segmentation from computed tomography images with metal artifacts. *IEEE Signal Processing Letters*, *23*(5), 678-682.

[16]. Brosch, T., Tang, L. Y., Yoo, Y., Li, D. K., Traboulsee, A., & Tam, R. (2016). Deep 3D convolutional encoder networks with shortcuts for multiscale feature integration applied to multiple sclerosis lesion segmentation. *IEEE transactions on medical imaging*, *35*(5), 1229-1239.

[17]. Tian, S., Dai, N., Zhang, B., Yuan, F., Yu, Q., & Cheng, X. (2019). Automatic classification and segmentation of teeth on 3D dental model using hierarchical deep learning networks. *IEEE Access*, *7*, 84817-84828.

[18]. Enguehard, J., O'Halloran, P., & Gholipour, A. (2019). Semi-supervised learning with deep embedded clustering for image classification and segmentation. *IEEE Access*, *7*, 11093-11104.

[19]. Dai, L., Fang, R., Li, H., Hou, X., Sheng, B., Wu, Q., & Jia, W. (2018). Clinical report guided retinal microaneurysm detection with multi-sieving deep learning. *IEEE transactions on medical imaging*, *37*(5), 1149-1161.

[20]. Mansoor, A., Patsekin, V., Scherl, D., Robinson, J. P., & Rajwa, B. (2014). A statistical modeling approach to computer-aided quantification of dental biofilm. *IEEE journal of biomedical and health informatics*, *19*(1), 358-366.

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