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ORAL CANCER DETECTION USING CNN

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Abstract: Oral cancer is a major global health issue accounting for 177,384 deaths in 2018 and it is most prevalent in low- and middle-income countries. Enabling automation in the identification of potentially malignant and malignant lesions in the oral cavity would potentially lead to low-cost and early diagnosis of the disease. Building a large library of well-annotated oral lesions is key. In this paper we developed neural networks based oral cancer detection using different image processing techniques. For that we are using Convolutional Neural Network for the automated detection of oral lesions for the early detection of oral cancer. Here we define oral cancer as malignant neoplasms of lip, tongue and mouth.

Keywords: Convolutional Neural Network, Detection of oral cancer, Image processing techniques

INTRODUCTION

Oral cancer is one of the most common cancers worldwide and is characterized by late diagnosis, high mortality rates and morbidity. GLOBOCAN estimated 354,864 new cases and 177,384 deaths in 2018. Two-thirds of the global incidence of oral cancer occurs in low- and middle-income countries (LMICs), half of those cases are in South Asia. Tobacco use, in any form, and excessive alcohol use are the major risk factors for oral cancer. A factor most prominent in South and Southeast Asia is the chewing of betel quid which generally is comprised of areca nut, slaked lime, betel leaf and may contain tobacco. Nowadays, these quid's are available commercially in sachets and are popular in public due to vigorous marketing strategies. Oral cancer is typically associated with late presentation, particularly in LMICs, where more than two-thirds present at late stages and as a result survival rates are poor. Management of cancers, especially at the late stages, is very costly.

The lack of public awareness and the lack of knowledge of health professionals concerning oral cancer is an important reason for late detection. Late diagnosis does not need to be a defining attribute as oral cancer is often preceded by visible oral lesions termed as oral potentially malignant disorders (OPMDs) which can be detected during routine screening by a clinical oral examination (COE) performed by a general dentist. If a suspicious lesion is identified the patient is referred to a specialist for confirmation of diagnosis and further management. Previous studies in India reveal screening has resulted in early diagnosis, down-staging of the disease and reduction in mortality amongst individuals who use tobacco and alcohol. With most of the burden of oral cancer falling on LMICs due to the limited number of specialists and health resources, it is vital that screening programs must offer a low-cost and efficient approach to diagnosis.

LITERATURE SURVEY

There are several research proposed for detecting oral cancer using image processing.

Amarasinghe.H , Jayasinghe.R.D, Dharmagunawardene.D, Attygalla. M, Scuffham P.A, Johnson N, Kularatna S [9]

A descriptive cross-sectional study with cost analysis was conducted using activity-based costing with cost apportionment and step-down costing approach. The study was conducted in selected cancer treatment centers in Sri Lanka; the University Dental Hospital Peradeniya (PDH), Apeksha Hospital, Maharagama and Oro-maxillofacial units of General Hospital Kalutara and Kegalle. As both Apeksha Hospital and PDH are centres of excellence for treatment of OCA and treat most of the cases in the nation, it was important to include these two institutions.

Jeyaraj P.R, Nadar E.R [15]
Oral cancer is a complex wide spread cancer, which has high severity. Using advanced technology and deep learning algorithm early detection and classification are made possible. Medical imaging technique, computer-aided diagnosis and detection can make potential changes in cancer treatment. In this research work, they have developed a deep learning algorithm for automated, computer-aided oral cancer detecting system by investigating patient hyper spectral images.

Haron N, Zain R.B, Ramanathan A, Abraham M.T, Liew C.S, Ng KG, Cheng LC, Husin R.B, Chong S.M, Thangavalu L.A, Mat A [12]
To evaluate the feasibility of using Mobile Mouth Screening Anywhere (MeMoSA) to facilitate early detection of OC. Methods: A mobile phone app named MeMoSA was developed and the feasibility of integrating this for documentation of oral lesions, and communication between dentists and specialists for management decisions were evaluated. The experience of dentists and specialists in using MeMoSA was determined using qualitative questionnaires.

Chu C.S, Lee N.P, Adeoye J, Thomson P, Choi S.W[4]
Researchers used to populate 4 machine learning algorithms, linear regression (LR), decision tree (DT), support vector machine (SVM) and k-nearest neighbors (KNN) models, to predictive oral cancer. Performances of model were validated based on accuracy, sensitivity and specificity, with predictive ability assessed by receiver operating characteristic (ROC) and area under the curve (AUC) calculation.

Shams W.K, Htike Z.Z [5]
In this paper used four classification techniques like support vector machine (SVM), Regularized Least Squares (RLS), multi-layer perceptron (MLP) with back propagation and deep neural network (DNN). Researchers also used Fisher discriminate analysis to select relevant features from the gene expression array. They got accuracy level is 96% using DNN and also achieved 94% accuracy for SVM and MLP with one sample cross validation. Furthermore, we achieved the same results using 10-fold cross validation.

Mohd F, Noor N,M, Bakar Z,A, Rajion Z,A [6].
Researchers proposed integrated diagnostic model with hybrid features selection methods to the diagnosis of oral cancer. With the help of feature selection researchers reduced 25 features to 14 features and also used four classifiers: Updatable Naïve Bayes, Multilayer Perceptron, K-Nearest Neighbors and Support Vector Machine to predict the oral cancer.

Ismail S,M, Daud N.M [7].
Proposed three fuzzy prediction models including fuzzy logic, fuzzy neural network and fuzzy linear regression models to predict the oral cancer. For prediction researchers used Malaysian oral cancer data set. After measure the performance of the model they decided that fuzzy linear regression has the capability of quantifying the relationships between input predictors and the predicted outcomes and also suitable for small sample size.

METHODOLOGY

In this section, image processing system is used to detecting oral cancer. The digital computer is used to processing of a two dimensional picture which is called as a digital image processing. A digital image always represented by finite number of bits. First step in image processing, image is converted to digitized and stored in computer memory and then processed a digitized memory and displayed on television monitor. To produce a visually continuous display, we should refresh the monitor at a rate of 25 frames per second by use rapid access buffer memory.

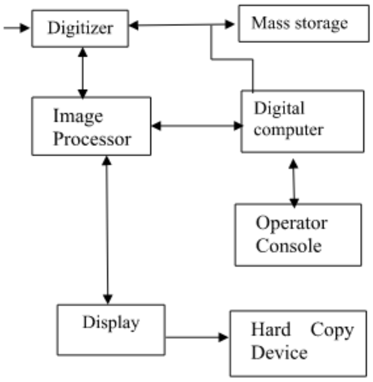

Fig 1: Block diagram for image digitizer

IMAGE PROCESSOR

An image processor performs the various functions such as image acquisition, storage, preprocessing, segmentation, representation, recognition, interpretation and finally displays the resulting image. In image processor the first step is image acquisition through an imaging sensor in conjunction with the help of a digitizer to digitize the image. Preprocessing is the second step of processor then the image is improved and applied as an input to the other processes. Preprocessing is used for enhancing, removing noise, isolating regions, etc. Segmentation split an image into its constituent objects and then get the raw pixel data, that constitute either the boundary of the region or the pixels in the region themselves. By use of the computer the raw pixel data is converted into a subsequent processing form.Based on the information provided, a label is assigned to an object by using its descriptors.

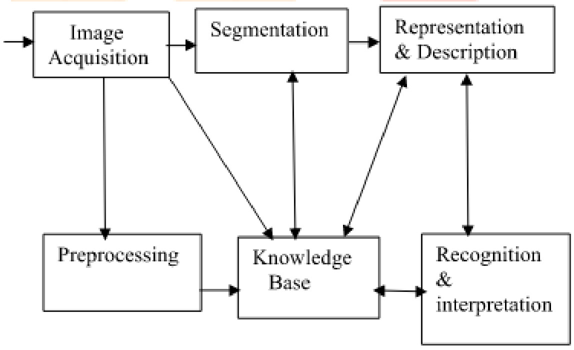

Fig.2: Block diagram of fundamental sequence involved in an image processing system

DIGITAL COMPUTER

The digital computer is used to perform the mathematical processing of the digitized image such as convolution, averaging, addition, subtraction, etc.

MASS STORAGE

Mass storage mostly use secondary storage devices like floppy disks, CD ROMs etc.

HARD COPY DEVICE

By using the hard copy device a permanent copy of the image is reproduced.

OPERATOR CONSOLE

The console is used for checking errors and entry of requisite data. It has equipment and arrangements for verification of intermediate results and consists of alterations in the software.

IMAGE ENHANCEMENT

It is used to increase the image brightness characteristics and contrast of an image and also reduce the noise content.

IMAGE RESTORATION

Image restoration increases the qualities of image based on known measured or degradations of the original image. It restores the images with problems such as geometric distortion, improper focus, repetitive noise, and camera motion.

IMAGE ANALYSIS

Based on characteristics of the original image which produce numerical or graphical information. It depends on the statistics of an image and break in to number of objects.

IMAGE COMPRESSION

It is used to reduce the storage space for data. All images consist of more number of redundant information and removed all the redundancies by using compression. The compressed image is decompressed when displayed. Lossless compression preserves the exact data in the original image, but lossy compression does not represent the original image but provide excellent compression.

IMAGE SYNTHESIS

Image synthesis is used to create images that are either physically impossible or impractical to acquire.

PROPOSED METHOD

In this paper computer vision based approaches were assessed for the automated detection of oral lesions for the early detection of oral cancer, these were image classification with Convolutional Neural Network is processed.

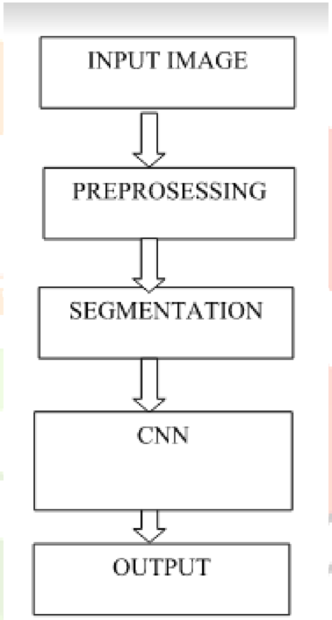

Fig.3: Block diagram of proposed system

INPUT IMAGES

Input image is retrieved from some open source by using hardware based source for processing. In the workflow sequence, this is the first step because, without an image, no processing is possible and then gets unprocessed images.

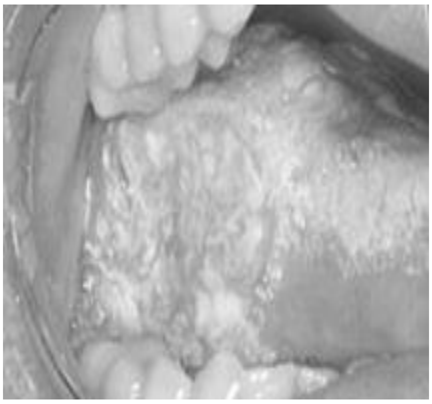

Fig.4: Gray scale image

PREPROCESSING

Pre-processing is used to increase the quality of an image and filter the distortions and extracts the features from the images. This method use redundancy concept in all images. The real image has essentially one object for brightness value. The average value of neighbouring pixels is restored in the form of distorted pixel.

RESIZING THE INPUT IMAGE

In this section resizing is done on input images to have same dimensions. Resizing the input image should produce the same as the input image otherwise get the distorted output.

FILTERING

It is a technique for modifying or enhancing an image. For example, you can filter an image to emphasize certain features or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge enhancement.

GAUSSIAN FILTERING

A Gaussian filter is a linear filter. It's usually used to blur the image or to reduce noise. If you use two of them and subtract, you can use them for "unsharp masking" (edge detection). The Gaussian filter alone will blur edges and reduce contrast.

IMAGE ENHANCEMENT

GAMMA CORRECTION

Gamma correction, or often simply gamma, is a nonlinear operation used to encode and decode luminance or tristimulus values in video or still image systems for improving the image visibility.

SEGMENTATION

Based on the characteristics of the pixels in the image, it divided in to multiple partsof the regions. In computer vision, Image Segmentation is used to divide a digital image into multiple segments also called as super pixels. Segmentation has similar attributes of grouping pixels.In segmentation each region is known as homogeneous Pixels in a region which are similar according to some homogeneity criteria such as color, intensity or texture so as to locate and identify boundaries and objects in an image.

CNN (CONVOLUTIONAL NEURAL NETWORK)

The **Convolutional Neural Networks** (CNN) is one of the most famous deep learning algorithms and the most commonly used in image classification applications. In general, the CNN architecture contains three types of layers and gets an input image that passes through the layers to identify features and recognize the image, and then it produces the result of classification. The CNN consists of many layers, followed by a set of fully connected layers. In the CNN, output of each layer act as an input of the following layer.

IMAGE INPUT LAYER

Image size of the input layer is 28-by-28-by-1. These numbers always represented to the height, width, and the channel size. The digit data consists of grayscale images, so the channel size (color channel) is 1. For a color image, the channel size is 3, corresponding to the RGB values. You do not need to shuffle the data because trainNetwork, by default, shuffles the data at the beginning of training. TrainNetwork can also automatically shuffle the data at the beginning of every epoch during training.

BATCH NORMALIZATION LAYER

By using the network this layer normalize the gradients and the activations and solve the optimization problem easier by training the network. With the help of RELU layer, need to increase speed up to training network and decrease the the sensitivity to network initialization.

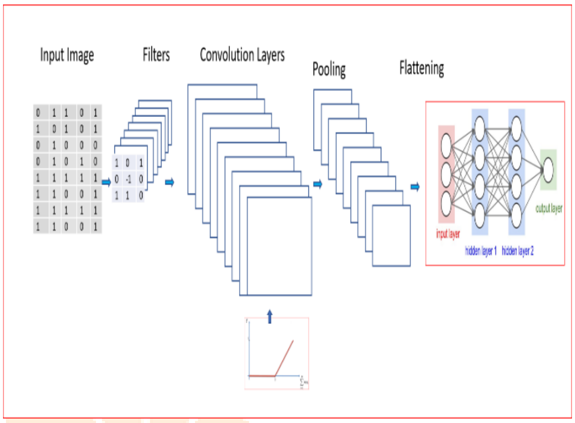

Fig. 5: CNN

RELU LAYER

Next layer in CNN is nonlinear activation function. The rectified linear unit is mostly used activation function in the network.

MAX POOLING LAYER

Down-sampling operation is used to reduce the spatial size of the feature map and removes redundant spatial information. In deeper convolutional layersnumber of filters are increased by using down sampling method without increasing the required amount of computation per layer.By the use of first argument the maximum values of rectangular regions of inputs are returns in max pooling layer

FULLY CONNECTED LAYER

The convolution and down-sampling layers are followed by one or more fully connected layers. All the neurons are connected in the preceding layer.To identify the larger patterns by combines all the features learned. For classify the images, this layer combines the features. So in this layer, the Output Size parameter should be equal to the number of classes in the specified data. In this example, the output size is 10, corresponding to the 10 classes.

SOFTMAX LAYER

The output of the fully connected layer is normalizes by using of softmax activation function. Positive numbers in the output of the softmax layer that sum to one, which can be used as classification probabilities. By using of softmaxLayer, we hate to create softmax layer after the last fully connected layer.

CLASSIFICATION LAYER

Classification layer is the last layer. In this layer we can uses the probabilities returned for each input to assign the input to one of the mutually exclusive classes and compute the loss.

RESULTS

This process can take less time to run when compared to existing system. This technique needs normal hardware requirements followed by low cost and user friendly when compared to existing technique.

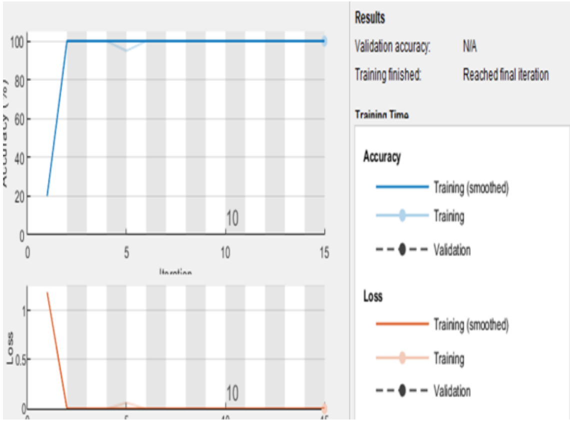

Fig.6: Output

CONCLUSION

In this paper, an automated CNN algorithm is used for the detection of oral cancer using image processing techniques. In this experimental result, background and bone parts are distinguished very efficiently which will positively help the physicians for automated oral cancer detection and further diagnosis.

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