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Automated classification of Oral Squamous cell carcinoma stages detection using Deep Learning Techniques

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Abstract
Deep learning have earned major popularity in the today world by captured best results in medical analysis field. This research explained the stages of Oral squamous cell carcinoma using the convolution neural network model in deep Learning. Whenever the pathologist examine the photomicrograph image they faced a lot of difficulties to process and finding the stages of oral squamous cell carcinoma into poorly differentiated, medium differentiated and low differentiated. To avoid the difficulties of stages differentiation, the convolution neural network model has been implemented in this research. In the methodology part of Deep learning basically needs large number of data to perform good result so in this work image augmentation was performed to improve the better performance level of deep learning. Finally segmentation has been implemented and the segmented values are given to the convolution neural networks and it gives better accuracy of 85% when compared with all other deep learning techniques.

Keywords: Oral Squamous Cell Carcinoma (OSCC), Convolution Neural Network (CNN), segmentation.

1. Introduction

Oral squamous cell carcinoma is the very cruel cancer disease in the world [1]. When compared with men mostly women had affected very less numbers [2]. The basic thing of Oral squamous cell carcinoma was tobacco habits of chewing with pan, cigerattes with using alcohol. Overall cancer disease mostly in squamous Cell Carcinoma and these cancers are additionally divided by most relavent resemble normal lining cells: well differentiated, medium differentiated and low differentiated. Figure 1(a) : represents the photomicrograph of oral squamous cell carcinoma.

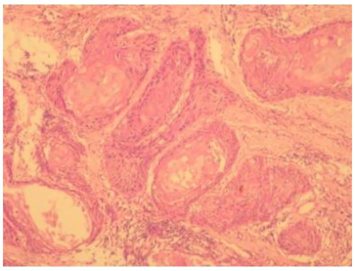

Figure 1: Photomicrograph of

Oral Squamous Cell Carcinoma

Histological process of tumor shows that 27%, 40 % and 21% of this research cancer cell was divided in to well, medium and low differentiated OSCC.

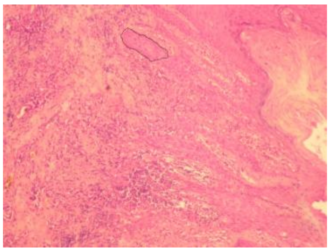

Fig 1(b): Poorly Differentiated

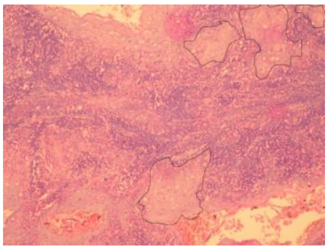

Fig 1(c): Moderately Differentiated

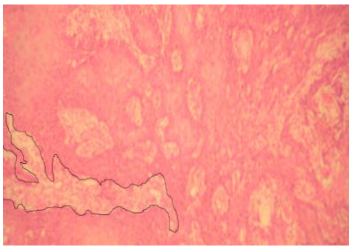

Fig 1(d): Well Differentiated

Figure 1(b): shows the image of poorly differentiated OSCC, Figure 1(c): Shows the image of moderately differentiated, Figure 1(d): Shows the image of well differentiated. For male it is mostly affected in the area of tongue, internal mucosa and buccal mucosa/ buccal sulcus in females. Figure 1 (e): shows the overall architecture of the proposed classification system.

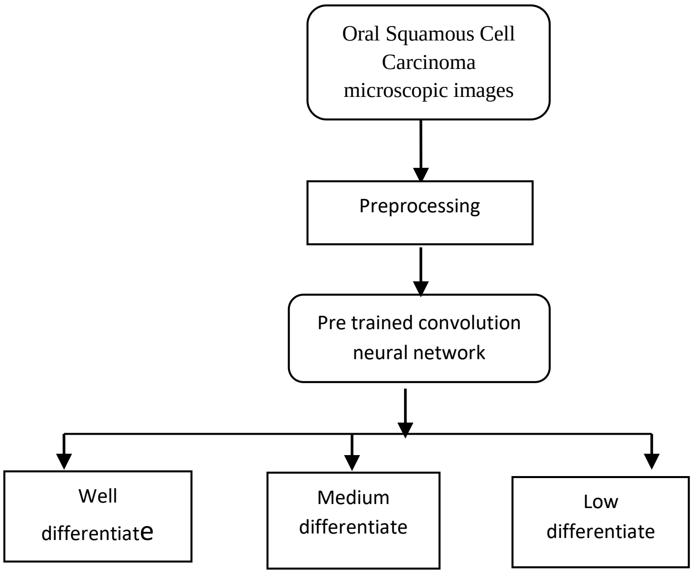

Figure 1(e): Block Diagram of OSCC classification System

2. Related Work

In [Siyuan Lu et al] the authors assess the brain detection using Alexnet were the last three layers were replaced by the random weights and the rest of the parameters served as the initial values. In [Merl James Macawile] proposed a work in calculation the WBC count in leukocytes through the pretrained convolutional neural network using Alexnet, GoogleNet, Resnet -101where Alexnet is the winner classifier. In [Paras Lakhani et al] evaluated the efficiency by detecting the Tuberculosis through two different DCNNs namely Alexnet and GoogleNet. In this work Pretrained Augmentation and untrained Augmentation results has been compared through ensembling both the results in which GoogleNet gives the best performance.

3. Deep Learning

Deep learning is a vast and famous approach for research field such speech, image processing and NLP [11]. Deep learning has the major technical concepts to change the entire image processing domain. In medical image processing analysis there is a number of techniques have been implemented. To representation of features directly from the data have to use the deep of learning techniques [12]. The most useful and challenging deep learning concept is Convolutional Neural Network here the various pretrained models which perform well compared with existing machine learning techniques. In the research methodology work, we concentrate on pretrained convolutional models [13].

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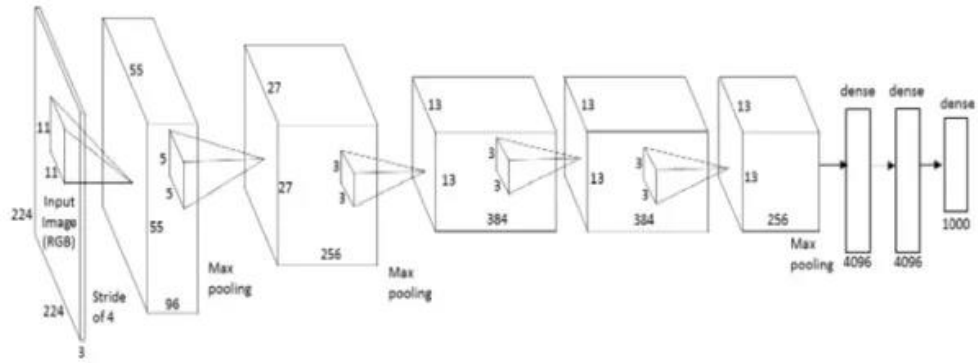
4. Pre-Trained Convention Neural Network Models

The pretrained networks are trained on more than a million images and can classify images into 100 object categories. The pretrained networks are trained on more than a million ImageNet databases, which is used in ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). Using a pretrained network with transfer learning is typically much faster and easier than training a network from scratch. The Three different pre-trained CNN models have been evaluated in this paper namely Alexnet, Resnet 50, Googlenet.

Alexnet

Alexnet is the one of the unique architecture in the area of deep learning. It started from traditional machine learning computer vision and later stepped into deep learning. It was the first neural network in the 21st century. Alexnet is a deep learning network defined from the ImageNet [14]. It consists of eight learning layers in which five convolution layers and three fully connected layers. The convolution layers are responsible for the feature extraction while the fully connected layers are the regular neural networks. The output of the final fully connected layers is the softmax regression which is used for the classification [15]. The main aspects of the softmax are to take results and fit it into the forwarded distribution of 1000 classes [16] Figure 1: shows the architecture of alexnet.



Max Pooling

Max Pooling is a familiar technique in CNN part for pooling methods, pooling is a condition of non-linear down sampling. Max pooling classified in to image format to non-overlapping sub regions for which the output of each region is the maximum value. Max Pooling is a important concept to eliminates a non-maximal value which in turn reduces the computation of the upper layers. This technique is a robust approach to reducing the dimensionality of intermediate responses.

Dropout

Dropout is a major concept that it is used for normalization. The idea is that the neural network contains multiple nodes. While provide regularization and fixed to the neural network is not biased to a particular result we have to perform the random dropping of the neurons in the network. This performs the dropout and we have to analyse the weightage of neurons to dropout and the network randomly chooses the neurons and dropout.

Resnet 50

It is the commonly used model in convolutional neural network. It is a very deep networks used in residual connections. It was first implemented by He et al., 2015.Residual Networks consists of multiple subsequent residual modules, which are constructed by Resnet architecture. Figure 2: shows the Resnet architecture.

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It has 152-layer model for ImageNet and it was ILSVRC 2015 topper in (3.57% top 5 error) [3]. the useage of resnet is even million of layers there also the resnet convert in to a network and then training process has been perform but sometimes the performance measurement might be reduced.

GoogleNet

GoogleNet is a technique in CNN which is designed by google researcher. Googlenet has 22 layers and introduce for the initial stage of efficient "Inception "module. Also there are fully connected layers with only 5 million parameters, is twelve times bigger than Alexnet. Figure 3: The construction of GoogleNet.

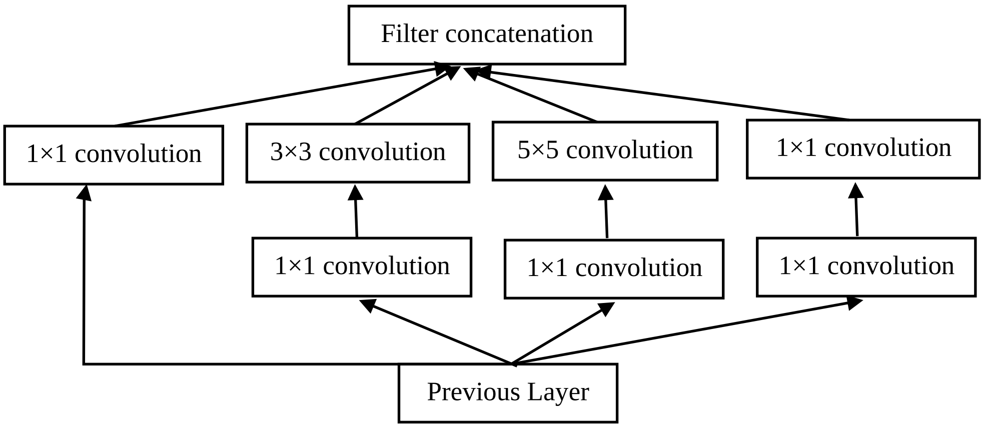

Figure 3: The building block of GoogleNet.

The figure 3 is grounded on "Inception module" which is simply designing a decent local network topology (network inside network) after that stacking these modules one above the other. In this apply, the parallel filter on the input from preceding layer: Various receptive field sizes used in convolution (1x1, 3x3, 5x5) – Pooling operation (3x3). Finally concatenate all filter outputs organized depth-wise.

5. Proposed Methodology

Preprocessing

Here the input image is obtained from the electron microscopic is of the size 256 x 256. Next the ROI is selected manually for disease identification and the region cropped.

ROI Cropping

For volumetric examinations, automatic freehand ROI technique, is presented in the system of microscopic image which is used. Using cell differentiation of OSCC, our proposed system categories automatically into well-differentiated group, moderately differentiated group and Poorly Differentiated group.

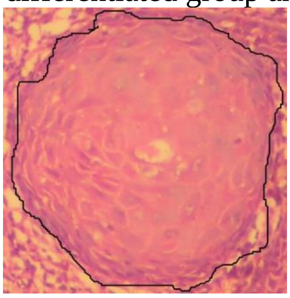

Figure 4: ROI selected input image.

7. Experimental Results

Datasets

The photomicrograph of OSCC shows the different stages that were collected from raja Muthiah Dental College and Hospital (RMDC & H) Annamalai university. Hematoxylin as well as eosin stained regions of OSCC showing well differentiated, poorly differentiated and moderately differentiated with (10 x magnification) higher magnification were taken.

Image Augmentation for Deep Learning

Deep networks basically require bulkier training data for good performance. Due to the scarcity of images, image augmentation is necessary for boosting the deep networks performance [5]. Augmenting randomized reprocessing operations such as resizing, reflection and rotation on training input images also prevents over fitting of network.

Recognition of Disease using Pretrained Alexnet CNN

The Alexnet consists of 8 layers of which the first five is the convolutional and the remaining three is the fully connected. It uses the different activation function called the ReLU (Rectified Linear Unit) after every convolution layers and it also has new types of processing called the dropout after FC layers 1 and 2.The input features are reduced from 154587 to 1024 before sending them to the fully connected by the arrangement of convolution and pooling layers. The detailed mapping of the proposed work of Alexnet is shown below:

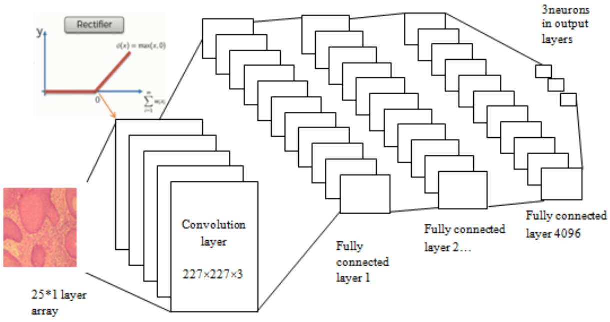

Figure: Proposed work of the Pretrained Alexnet CNN.

In the above figure, the input image size is fixed to 227 x 227x3 in the input layer. In the input layer it contains the three feature map. The first is the convolution layer contains the activation function with 96 feature map and each map size is 55x55 where the filter size is 11x11 and the stride is 4 x 4.In the first max pooling the feature map remains as 96 with each of size 27 x 27, its filter size is 3 x 3 and the stride changes to 2 x 2.

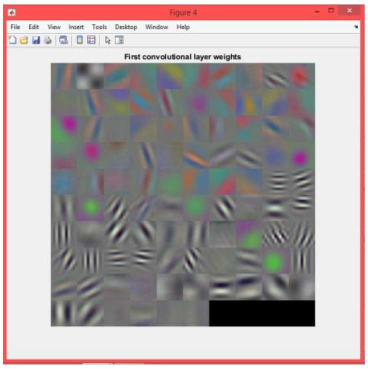

Figure : Alexnet First Convolutional Layer Weights

In the second convolution layer the 256 feature map of size 23 x 23 has been obtained with the filter size is 5 x 5, stride is 1 x 1. In the second pooling the feature map remains unchanged but reduced in size to 11 x 11, the filter size reduces to 3 x 3, and the stride is 2 x 2. In the third convolution layer the feature map is increased to 384 with size 9 x 9 each, the filter size is 3 x 3 and stride is 1 x 1. In the fourth convolution layer the feature remains unchanged with size 7 x 7 , filter size 3 x 3 with the stride of 1 x 1. The fifth convolution layer the feature map is 256 with size 5 x 5 and filter size is 3 x 3 with the stride of 1 x 1. The third max pooling the feature map remains unchanged, the size of 2 x 2, the feature size is 3 x 3, the stride 2, 2.The output of the final max pooling layer is given 4096 fully connected nodes. The softmax classifier is used to categorize into three classes.

Recognition of disease using pretrained Resnet50 CNN
Resnet50 has 177 layers in which 50 layers forms the residual layers. The input image of 224x 224 is taken as the input. Here the first convolution layers consists of 64 filters with 7 x 7 filter size with the stride 2 x 2 is processed.

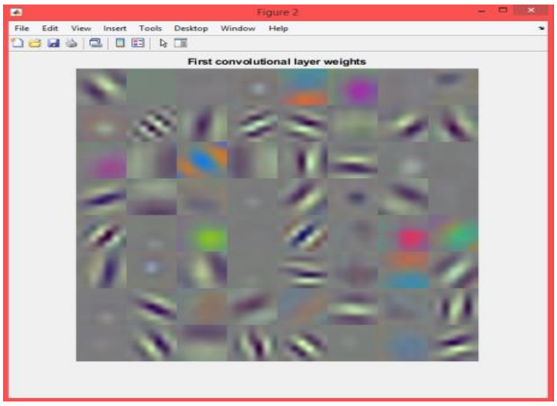

Figure: Resnet50 First Layer Weights

Further the batch normalization is processed with 64 channels with Rectifier Linear unit as the activation function and with the max pooling of 3 x 3.Hence this steps is processed for the remaining all the resnet-50 layers. The final convolution yields 2048 parameters with the batch normalization of 2048 channels, with the average pooling of 1000 FC layer. Later softmax classifier is used to categorize the three classes into poorly differentiated, moderaly differentiated and well differentiated.

Recognition of disease using Pretrained Googlenet convolution neural network
The googlenet consists of 144 layered arrays with 22 layers deep. Figure : Proposed work of Pretrained Googlenet CNN.

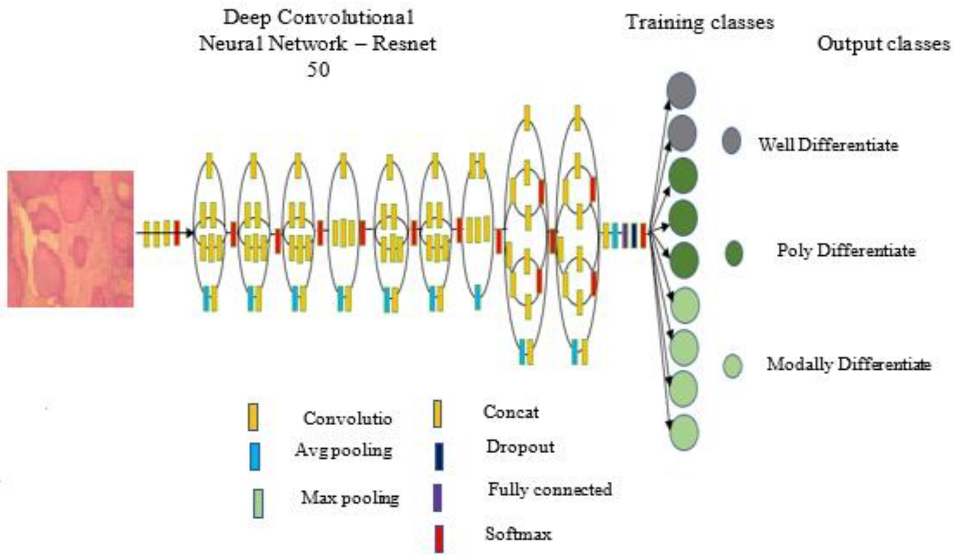

Figure: Proposed work of the Pretrained Googlenet CNN.

Here the input is resized into 224 x 224. The first covolutional layer consists of 64 filters with the size of 7 x7 x 3convolutions with stride [2 2] with which it is activated using the Rectified Linear Unit with the max pooling and the channel is normalized with 5 channels per element and the process in continued for the next second convolution.

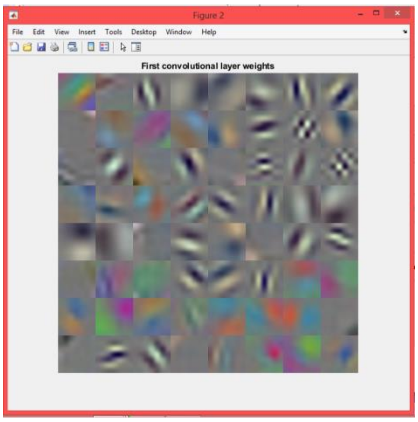

Figure: Googlenet First convolutional Layer Weights.

Next step it enters into the inception block with the convolution of 64 filters of 1 x 1 size of 192 convolution with the stride of [11] and this activated using Rectified Linear unit. This process is continued. The final convolutional layers is processed with depth concatenation with the average pooling of 40 % droout ratio and it gets flattern with the dense layer further it is categorized into three classes namely well differentiated, moderally differentiated and poorly differentiated.

Testing

For testing the histopathological images of different stages were taken for prediction. The prediction of classes was computed by pre-trained neural network in MATLAB 2018b prediction analysis. The prediction matrix is given into three classes namely well differentiated, poorly differentiated, moderly differentiated.

Performance Measures

The performance accuracy is calculated using confusion matrix based on predicted samples. The below table represents the performance evaluation of oral squamous cell carcinoma:

Table 1: Performance evaluation on classification of OSCC stages using Pretrained CNN

Proposed Method Of Pre-trained Neural Network	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
Alexnet	82.91	91.11	91.11	91.11
Resnet 50	83.20	93.23	93.23	93.23
Googlenet	86.50	95.00	95.00	95.00

8. Conclusion

This research was able to classify the OSCC stages on microscopic images using pretrained CNNs. Moreover upon comparison of the three CNN models (Alexnet, GoogleNet and Resnet-50) it was observed that GoogleNet performed best on the task of the classification of OSCC stages sample images as Compared to Alexnet and GoogleNet generating an global accuracy of 95%.

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