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Detection of oral cancer using deep learning approach

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***Abstract*---**Globally, oral cancer is becoming more and more of an issue, and in some nations, like Taiwan, India, and Sri Lanka, it is at the very top of the list. Tobacco, alcohol, and betel nut use are responsible for more than 95% of all mouth cancer cases (BQ). In Western nations, smoking and alcohol consumption are the two biggest risk factors, but in Asian nations, smoking and BQ usage are the two most risk factors. It is alarming how frequently people with advanced oral cancer arrive. The best method for minimising personal illness burden, lowering morbidity and mortality, and enhancing quality of life. The detection, evaluation, and treatment of oral cancer remain challenges for the dental profession. In the proposed approach, deep learning algorithm has been used to simulate the development of cancer diagnosis and therapy, and they are successful in predicting future outcomes of a cancer. For the best outcomes in the detection and diagnosis of oral cancer, an effective deep learning and feature selection approach utilising Alex net model has been applied.Overall, 500 images with different resolution were used in our system. Out of these images, data set consists of 125 histopathological images with the normal epithelium of the oral cavity and 375 images of Oral Squamous Cell Carcinoma (OSCC). Our proposed model is able to predict the oral cancer with 96.60 % accuracy. Our model has been tested using different statistical

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parameters like F1-score, Precision and Recall for the purpose of validation.

***Keywords*---**Alex net, deep learning, diagnosis, histopathological, precision, oral cancer.

Introduction

Sincemore than half of patients receive advanced-stage diagnoses, the prognosis for oral cancer remains dismal. There is currently no proven approach for oral cancer screening and early diagnosis, contrary to previously published reports, which heavily rely on clinical expertise of healthcare professionals. Development of a rapid, non-invasive, cost-effective, and user-friendly deep learning system for squamous cell carcinoma of the oral cavity (OCSCC) detection using photographic images need to be settled. One of the most frequent cancers in the world is oral cancer. In 2018, there were an anticipated 177,384 cancer-related deaths and 354,864 new cases, which is a 2 percent increase in both cases and fatalities from the disease. About 90% of instances of oral cavity cancer are squamous cell carcinoma (SCC). Due to the relatively little effort put into screening and detection, which explains the persistent rate of diagnosis with advanced-stage diseases, the overall mortality of oral cavity squamous cell carcinoma (OCSCC) has not decreased significantly since the 1980s, despite the adoption of various emerging treatment modalities over the past decades.

OCSCC must be found, and this is crucial. As the predicted 5-year survival rate for OCSCC shows a clear decline from around 39% if found in its advanced phases (stages III and IV) to about 84% if detected in its early stages (stages I and II). And to make matters worse, patients with advanced-stage illnesses must endure lower postoperative quality of life due to the painful and expensive multimodal therapy procedure that includes surgery, adjuvant radiation therapy, and chemotherapy. The mouth cavity may be seen clearly without the need of special tools, unlike other internal organs. According to their own expertise and understanding of the visual characteristics of malignant tumors, specialists often suspect mouth cancer during visual inspection in clinical practice. OCSCC lesions often start off as white, red, or mixed white-red patches. As time goes on, the mucosal surface typically takes on a more irregular, granular, and ulcerated look. The main objective of the proposed system is to use deep learning technique to detect the presence of oral cancer. Here, authors have created a deep learning method employing data sets for completely automated OCSCC identification with the presumption that deep neural networks could recognize certain visual patterns of oral cancer like human specialists.On internal and external validation datasets, authors assessed the algorithm's performance, and on a clinical validation dataset, and finally, compared the model's results through standard deep learning metrics.

Methodology

Oral cancer diagnosis and detection can increase patient survival and lower morbidity rates. As a result, modern computer science techniques are presently used for precise diagnosis. Deep learning algorithms are used to simulate the development of cancer diagnosis and therapy, and they are successful in predicting the course of many cancer types in the future. The suggested strategy combines effective Deep learning with effective feature selection algorithms to deliver superior outcomes in the diagnosis and prognosis of oral cancer. Figure 1 depicts a deep neural network-based method for the identification of oral cancer in this instance.

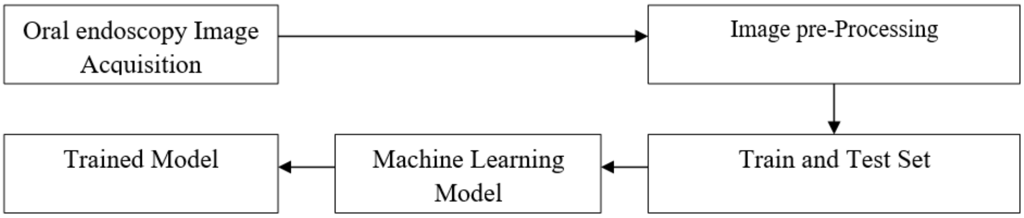

Figure 1: Overview of the Oral cancer detection System

Image Acquisition

The oral cancer image is acquired during the acquisition step. First, using first-order optics, the optical system characteristics, including magnification and field of vision, were best constructed. The optical conservation theorem was used to derive the irradiance restrictions. When the camera lens and CCD sensor were known, we could estimate the working distance restriction based on the relationship between the subject and the detector.

Pre-Processing

The original captured images have a high quality and are the right size for image processing, making them big enough for manual analysis by professionals. Processing large-scale pictures in computer systems, particularly when using neural networks, is an extremely expensive process that requires significant material and software investment. The following are the primary sources of image flaws. 1. Image standardization 2. Remove text 3. Presence of image artifacts 4. Geometric Distortion 5. Low contrast 6. High level of noise 7. Image Segmentation.

Machine Learning Model

There are eight learnable levels in the Alexnet. Relu activation is used in each of the five levels of the model, except for the output layer, which uses max pooling followed by three fully connected layers.

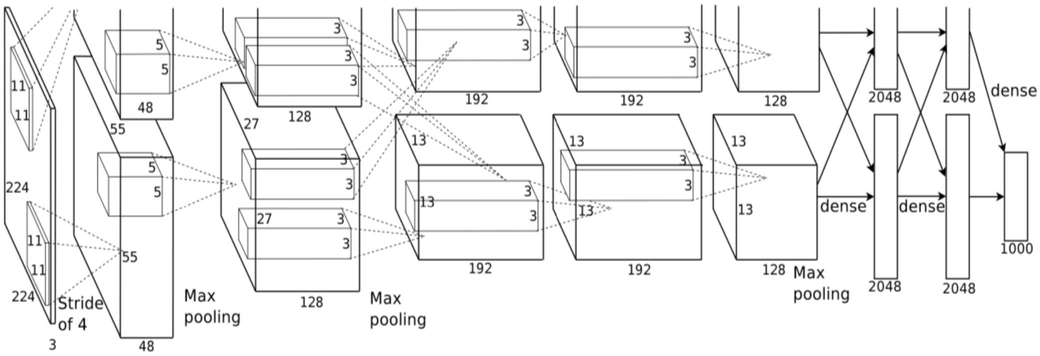

Figure 2: Architecture of Alexnet System

They discovered that the training process was nearly six times faster when the relu was used as an activation function. Additionally, they made use of dropout layers, which stopped their model from overfitting. The image with a size of 227X227X3 are used as the model's input.Figure 2 depicts a typical Alexnet machine learning architecture model.

Performance Evaluation

Accuracyof the model is computed using number of correct predictions to the total number of predictions. Eq.(1) is used to compute the accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \quad (1)$$

$$\Pr ecision = \frac{TP}{TP + FP} \quad (2)$$

Aprecision score towards 1 will signify that your model didn’t miss any true positives. A low precision score (<0.5) means your classifier has a high number of false positives which can be an outcome of imbalanced class or untuned model hyperparameters.

A Recall is essentially the ratio of true positives to all the positives in ground truth as given in Eq. (3).

$$\operatorname{Re} call = \frac{TP}{TP + FN} \quad (3)$$

F1-score metric uses a combination of precision and recall. In fact, the F1 score is the harmonic mean of the two**.** F1 score is evaluated using the Eq. (4).

$$F1 = \frac{2 * \Pr ecison * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \quad (4)$$

When compared to all positive data points, TPR measures the percentage of positive data points that are accurately interpreted as positive.In other words, we will miss fewer positive data points the higher the TPR. TPR is calculated using Eq. (5).

$$TPR = \frac{TP}{TP + FN} \qquad (5)$$

FPR measures the percentage of negative data points that are inadvertently interpreted as positive.In other words, the more negative data pieces we misclassify. FPR is calculated using Eq. (6).

$$FPR = \frac{FP}{FP + TN} \qquad (6)$$

Results and Discussion

For the proposed work a data set with mouth cancer and without mouth cancer images have been collected from the histopathology. This data set consisting of 500 images with different resolution. Out of these images, data set consists of 125 histopathological images with the normal epithelium of the oral cavity and 375 images of Oral Squamous Cell Carcinoma (OSCC).From this dataset, 80% of the images have been used as train set and remaining 20% of the images have been used as test set. A dataset consisting of images of different category of mouth cancer has been used to train the model. At the time of feature extraction image of each image will be resized to 227 * 227. In our approach Alexnetmodel has been Proposed and trained to detect the presence of cancer in the images. Different evaluation metrics like True Positive Rate (TPR), False Positive Rate (FPR), Accuracy, mAP, precision, F1 score and recall have been presented. The mean average precision (mAP) is one of parameter or metric used to evaluate the model for the purpose of detection. mean average precision (mAP) of the model for both training and validation for accuracy and loss function ispresented in Figure 3 and Figure 4 respectively.

Figure 3 mean average precision (mAP) curve for Accuracy

Figure 3 represents map for training as well as for validation set for a period of 25 epochs. Our proposed model is providing an accuracy of 96.6% towards the detection of cancer. Similarly, training loss and validation loss along the epochs is presented in Figure 4. Loss needs to be minimum for a model and we achieved 0 loss for the training set and 0.5 for the validation set.

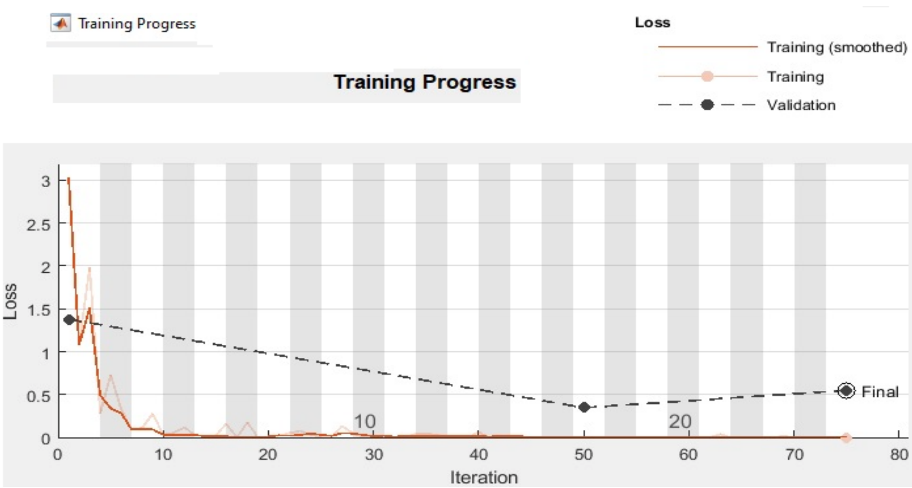

Figure 4 mean average precision (mAP) curve for Loss

After applying Deep Learning Algorithms on datasetanalysis has been made through Confusion Matrix, Accuracy, Precision, Sensitivity, F1 Score, AUC as performance metrics to evaluate and compare the models and identify the cancer Prediction.

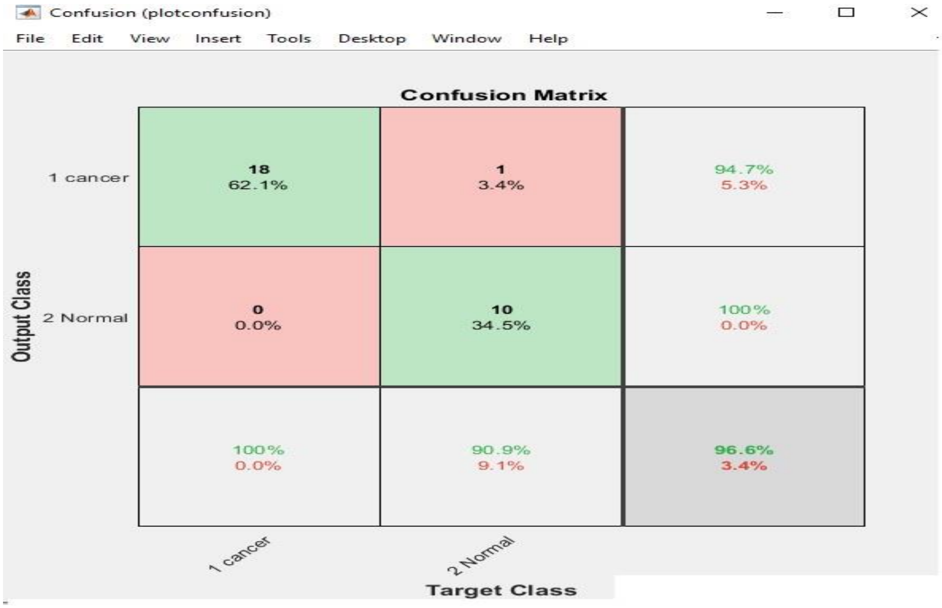

Figure 5 Confusion Matrix

F1 score is the weighted average of the precision and Sensitivity. Table 1 show the accuracy percentage, map, Batch loss and AUC for training and validationseparately onhistopathological datasets. Table 2 presents precision, recall and F1 score corresponding to cancer and normal images of the patient.

Table 1: map, batch loss and AUC

Network	Accuracy (ConfMatrx)	MAP		Batch Loss		AUC	
		Training	Validation	Training	Validation	Training	Validation
Proposed Model	96.6	96.55	95.55	0.0541	0.5497	0.0541	0.5497

Table 2: Metrics Table

Type	TP	FP	FN	TN	TPR	FPR	Precision	Recall	F1-Score	Accuracy
Cancer	18	0	1	10	0.642	0	1	0.9474	0.973	96.55
Normal	10	1	0	18	1	0.052	0.909	1	0.992	96.55

Conclusion

We conclude by stating that deep learning techniques could make it possible to automatically identify OCSCC patients with performance matching or even exceeding that of knowledgeable human specialists.An easy-to-use, non-invasive, and affordable method to quickly identify OCSCC lesions and enable therapy might be made available to non-specialists by the created algorithm with strong generalisation capabilities. Finally, our modelachieveda efficiency of 96.6%, Precision of 100.0% for cancer detection and with 90% for normal.

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