ORAL CANCER PREDICTION USING DEEP LEARNING

ABSTRACT:

Oral cancer has been one of the most mortal diseases in the world, and accurate and timely treatment will efficiently improve the survival and cure rate of the patients. However, the traditional diagnosis ways by the clinicians could be laborious and easily misdiagnosed, and oral cancer usually with different morphological features, which makes it challenging to achieve the high accuracy classification automatically. To address this challenge, in this paper, we have classified the histopathological images of Oral squamous cell carcinomas(OSCC) using convolutional neural network from deep learning concept to find do differentiate between normal and OSCC.

Keywords:* *Oral cancer, Diagnosis, Morphological features, histopathological images squamous oral carcinoma cell.

1. INTRODUCTION

The lining of the lips, mouth, or upper throat can develop cancer, which is known as oral cancer or mouth cancer. In the mouth, it typically begins as a painless white area that thickens, turns red in spots, develops into an ulcer, and keeps getting worse. It typically appears on the lips as a slow-growing, persistent crusting ulcer that does not heal.

Oral cancer is a malignant tumour that develops in the tongue, floor of the mouth, hard palate, upper/lower gums, and buccal mucosa. Salivary glands, oropharynx, nasopharynx, and hypopharynx are among the areas affected. The chief signs and symptoms of this condition include recurring or long-lasting ulcers on the oral mucosa, lumps or nodules, discomfort, numbness, and difficulties swallowing. According to reports, cigarettes, alcohol, and betel quid, and are the leading oral cancer risk factors. According to certain research, the human papillomavirus, and certain dietary habits can both increase the risk of oral cancer. Patients' oral cancer diagnoses are being delayed throughout the world. This is a result of a lack of adequate medical resources. and lack of qualified medical personnel and diagnostic tools. For example, when most patients feel discomfort in the oral cavity, they will contact the family doctor or dental clinic. In many cases, these facilities may not have resources for oral pathological biopsy. This means that only a preliminary oral examination can be done, even though the diagnosis sensitivity highly depends on the doctor’s experience. According to a study by Lingen et al., by the time more than 60% of patients were diagnosed, the tumour had progressed to the third and fourth stages. Additionally, the lesion area had reached a size visible to the naked eye. It is estimated that about 80% of patients can live for five years if oral cancer can be detected and located at an early stage. Therefore, it is necessary to study and develop effective and quick detection methods for early-stage oral cancer and oral precancerous lesion. Meanwhile, cost and portability should also be considered for the detection methods if they are to be promoted and used globally.

A growing body of research on employing artificial intelligence to improve medical diagnostics has been conducted recently (AI). The growing prevalence of diagnostic imaging has made it possible for researchers to look into the use of AI for the analysis of medical pictures. One AI method in particular, Deep

Learning (DL), has demonstrated notable effectiveness in tackling a variety of medical image processing issues, particularly in the diagnosis of cancer in pathological images. Computer-Aided Diagnosis (CAD) systems for a variety of cancer types, including breast cancer, lung cancer, prostate cancer, etc., have been suggested and developed on a large scale based on DL. However, the literature shows that DL hasn't been widely used for OSCC diagnosis from pathological pictures. Convolutional Neural Network (CNN) and Random Forest were employed by Dev et al. in a study to identify keratin pearls in images of oral histology. For keratin area segmentation, the CNN model had a 98.05% accuracy rate, while the Random Forest had a 96.88% accuracy rate. Similar to how Das et al used DL to categorise oral biopsy images according to Broder's histological grading scheme, Additionally, CNN was suggested, and it demonstrated a 97.5% classification accuracy. Jonathan et al. used CNN to classify oral cancer tissue into seven categories using Active Learning (AL) and Random Learning (RL) (stroma, lymphocytes, tumour, mucosa, keratin pearls, blood, and adipose). It was discovered that the AL's accuracy outperformed the RL's by 3.26%. Additionally, Francesco et al. divided the whole slide images (WSI) of oral lesions into three classes (carcinoma, non-carcinoma, and non-tissue) using various deep learning architectures, including SegNet, U-Net, U-Net with VGG16 encoder, and U-Net with ResNet50 encoder. A deeper network, like U-Net updated with ResNet50 as the encoder, was demonstrated to have more accuracy than the original U-Net. Recently, Rutwik et colleagues used ResNet to conduct binary classification on pictures of oral disease and reached an accuracy of 91.13%.

This study aimed to investigate challenges facing CNN models and tried to address them to reach superior results in histology diagnosis, which is critical for early diagnosis of OSCC. To achieve this study's aim, the data set images were enhanced to remove noise and address time consuming problems and the requirement of costly computers using hybrid techniques between deep learning and machine learning. Moreover, diagnoses of OSCC were based on fusion features between deep learning models and features of colour, texture, and shape extracted by the DWT, LBP, FCH, and GLCM algorithms. The main contributions of this study are as follows:

- Two overlapping filters were applied to improve histological images of oral cancer.
- Effective diagnosis of histological images of oral cancer cells using a hybrid technique between CNN models and the SVM algorithm.
- The PCA algorithm was applied to reduce the dimensionality of the elevated OSCC data set features.
- Diagnosing the histological images of oral cancer cells using the ANN algorithm based on the hybrid features extracted by CNN models and combining them with the colour, texture, and shape features extracted by the DWT, LBP, FCH, and GLCM algorithms.
- Designing high-efficiency systems to help specialist doctors in making accurate diagnostic decisions.

2. MATERIALS AND METHODS

This section reviews the materials and methodologies used in this study for classifying histopathological images for early diagnosis of OSCC, as depicted in Figure 1. As the OSCC data set images contained artifacts, the first step was to optimize all histological images. To achieve this study's aim, there were two approaches deployed with two systems for each. The first approach was based on a hybridization of both CNN models and SVM algorithms, while the second approach was to diagnose data set OSCC by the ANN based on hybrid features extracted by CNN models with colour, shape, and texture features extracted by the DWT, LBP, FCH, and GLCM.

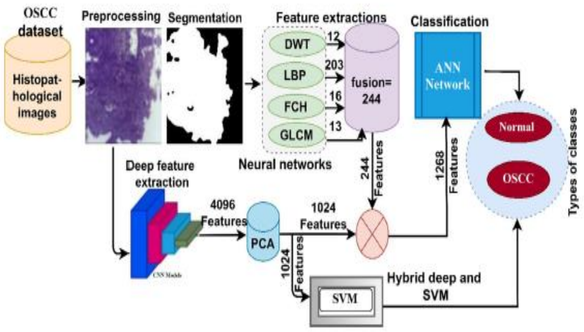
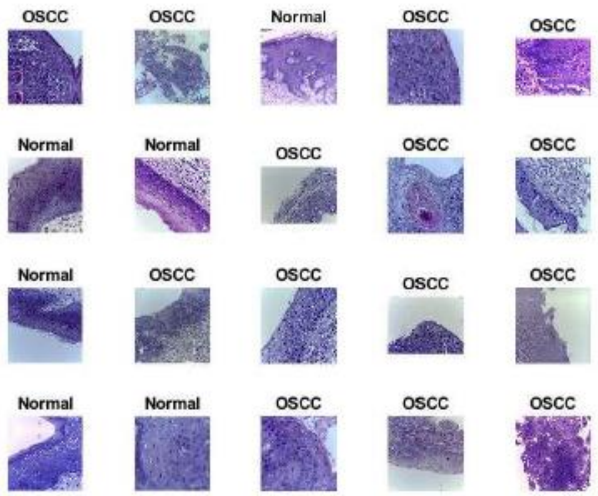


Figure 1

2.1 Pre-processing of Histopathological Images

Pre-processing is one of the most critical steps in biomedical image processing, which helps to coordinate images appropriately to obtain high accuracy. CNN models require expensive computations and consistent formatting of input images. The biopsy slides contain dark areas, and some of them are stained with blood and some medical solutions; therefore, there is a difference in the color of the images of the slides. Thus, the average RGB color for each image was calculated; then, the color consistency was calculated by adjusting the scale for each image.



Histopathological Images

2.2 CNN Architecture

Input

A Matrix of pixel values in the shape of [WIDTH, HEIGHT, CHANNELS]. Let's assume that our input is [32x32x3].

Convolution

The purpose of this layer is to receive a feature map. Usually, we start with low number of filters for low-level feature detection. The deeper we go into the CNN, the more filters we use to detect high-level features. Feature detection is based on 'scanning' the input with the filter of a given size and applying matrix computations in order to derive a feature map.

Pooling

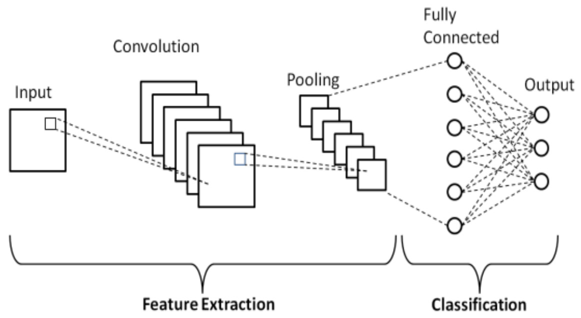
The goal of this layer is to provide spatial variance, which simply means that the system will be capable of recognizing an object even when its appearance varies in some way. Pooling layer will perform a down sampling operation along the spatial dimensions (width, height), resulting in output such as [16x16x12] for pooling size=(2, 2).

Fully Connected

In a fully connected layer, we flatten the output of the last convolution layer and connect every node of the current layer with the other nodes of the next layer. Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular Neural Networks and work in a similar way.

Image Classification

The complete image classification pipeline can be formalized as follows: Our input is a training dataset that consists of N images, each labeled with one of the 2 different classes. Then, we use this training set to train a classifier to learn what every one of these histology images belongs to i.e. benign or malignant. In the end, we evaluate the performance of the classifier by using it to predict labels for a new set of images that it has never seen before. We will then compare the true labels of these images to the ones predicted by the classifier. Furthermore, the obtained results are reported in terms of standard metrics.



3. DEEP LEARNING MODEL

After loading of the histology images, we will create a numpy array of zeroes for labelling "benign" and "malignant" images and then shuffling the dataset for converting the labels into a categorical format.
We will split the dataset into two sets — train and test sets with 80% and 20% images respectively. Let's see some sample benign and malignant images.

3.1.CNN MODEL BUILDING

We will use the "DenseNet201" as the pre trained weights which is already trained on the Imagenet dataset with a learning rate of 0.0001. Furthermore, global average pooling layer followed by 50% dropouts to reduce over-fitting. Using batch normalization and a dense layer with 2 neurons for 2 output classes i.e. "benign" and "malignant" with Softmax as the activation function and Adam as the optimizer and binary-cross-entropy as the loss function.

CNN MODEL TRAINING

Before training of the model, it is useful to define one or more callbacks. some useful one's are: ModelCheckpoint and ReduceLROnPlateau.

ModelCheckpoint: When training requires a lot of time to achieve a good result, often many iterations are required. In this case, it is better to save a copy of the best performing model only when an epoch that improves the metrics ends.

ReduceLROnPlateau: Reduce learning rate when a metric has stopped improving. Models often benefit from reducing the learning rate by a factor of 2–10 once learning stagnates. This callback monitors a quantity and if no improvement is seen for a 'patience' number of epochs, the learning rate is reduced.

MODEL PERFORMANCE EVALUTION

The most common metric for evaluating model performance is the accuracy. However, when only 2% of your dataset is of one class (malignant) and 98% some other class (benign), misclassification scores don't really make sense. You can be 98% accurate and still catch none of the malignant cases which could make a terrible classifier.

Precision, Recall and F1-Score

For a better look at misclassification, we often use the following metric to get a better idea of true positives (TP), true negatives (TN), false positive (FP) and false negative (FN).
Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.
Recall is the ratio of correctly predicted positive observations to all the observations in actual class.
F1-Score is the weighted average of Precision and Recall.

$$F1 = \frac{2 * (Recall * Precision)}{(Recall + Precision)}$$

The higher the F1-Score, the better the model. For all three metrics, 0 is the worst while 1 is the best

PLOTTING THE CONFUSION MATRIX

Confusion Matrix is a very important metric when analysing misclassification. Each row of the matrix represents the instances in a predicted class while each column represents the instances in an actual class. The diagonals represent the classes that have been correctly classified. This helps as we not only know which classes are being misclassified but also what they are being misclassified as.

ROC CURVE

The 45 degree line is the random line, where the Area Under the Curve or AUC is 0.5 . The further the curve from this line, the higher the AUC and better the model. The highest a model can get is an AUC of 1, where the curve forms a right angled triangle. The ROC curve can also help debug a model. For example, if the bottom left corner of the curve is closer to the random line, it implies that the model is misclassifying at Y=0. Whereas, if it is random on the top right, it implies the errors are occurring at Y=1.

4. CAUSES OF ORAL CANCER

Warning signs and symptoms of oral cancer and associated maxillofacial malignancies

Simple to extremely complicated variations of oral ulcerations may be indicative of oral cancer. In other words, patients typically complain of "ulceration," which refers to damage to the epithelium and connective tissue with the presence of a clear central crater brought on by swelling or growth in the nearby tissue. Medical professionals need to be able to distinguish between reactive lesions that persist for longer than two weeks after the removal of the etiological causes and malignant/premalignant lesions. When these lesions intensify and stop responding to continued treatment, they are considered more suspicious. Therefore, appropriate diagnostic procedures (i.e., gold standard biopsy in addition to other non-invasive chairside procedures of the lesion) are essential diagnostic aids in the evaluation of any lesion that does not respond to usual therapy in 7 to 14 days . Common oral and maxillofacial malignancies presented as persistent non healing oral ulcers are

I. Squamous cell carcinoma – It appears as red or white, painless, indurated, non-healing ulcer with elevated and ill-defined margins. Most of the oral carcinomas may present long standing non-healing ulcero-proliferative lesion with a rolled or indurated border. Common primary tumour sites of the oral cavity as reviewed in literature is attributed to buccal mucosa, tongue, lower alveolus, gingiva, floor of the mouth and palate.

II. Salivary gland tumour - Salivary gland malignancies (muco-epidermoid carcinoma and adenoid cystic carcinomas) occur predominantly in the palate, cheek and gingival region of the jaws as a chronic ulcer.

III. Lymphomas- Lymphomas may present as chronic ulcer covered with necrotic slough in the palatal region of the jaw in specific tumours of palate and paranasal sinus .

IV. Leukemia- Unlike, lymphatic tumours, leukemic tumours occur commonly in the gingival region of the mouth mimicking the clinical picture as lymphomas -.

V. Basal cell carcinoma and Metastatic tumours - may also present as ulcer.

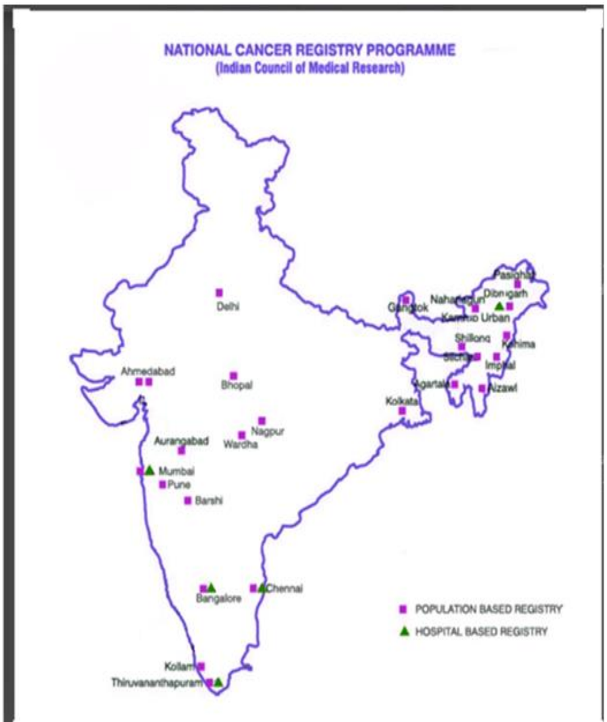
• Non healing ulcer with or without induration / nonhealing socket.
• White patch with firm consistency.
• Red lesion or lesion with erythematous appearance (Erythroplasia).
• Abnormal lump in the mouth with increase in size.
• Exophytic/ulceroproliferative growth.
• Mass or lump in the neck and neigbouring regions (Lymph node enlargement).
• Mobility/ displacement/ non vital teeth/peri implantitis.
• Tooth pain and referral pain.
• Bleeding from the mouth (hemorrhage).

Potential warning signs/symptoms of the oral cancer.

5. PREVALENCE OF ORAL CANCER IN INDIA

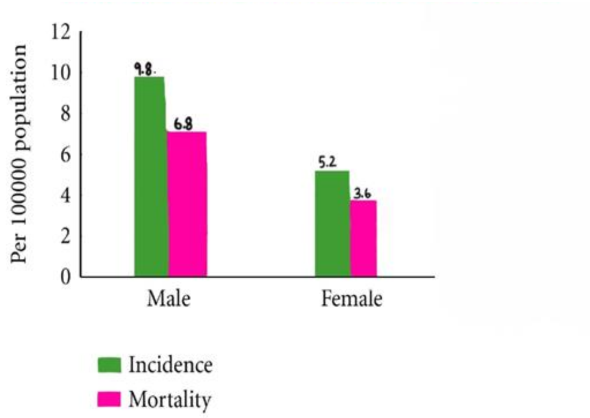
South and Southeast Asian nations, including India, have the highest rates of oral cancer. Squamous cell carcinoma accounts for 90–95% of mouth cancer cases in India . According to the worldwide agency for cancer research, India would experience an increase in cancer incidence from 1 million in 2012 to more than

1.7 million by 2035. This suggests that the number of cancer-related deaths will likewise rise throughout this time, from 680000 to 1- 2 million. Oral cancer and poor poverty are linked, according to a case-control research from India. Oral cancer growth is influenced by variables such poor diet, inadequate health care, unhealthy living conditions, and risky behaviours.

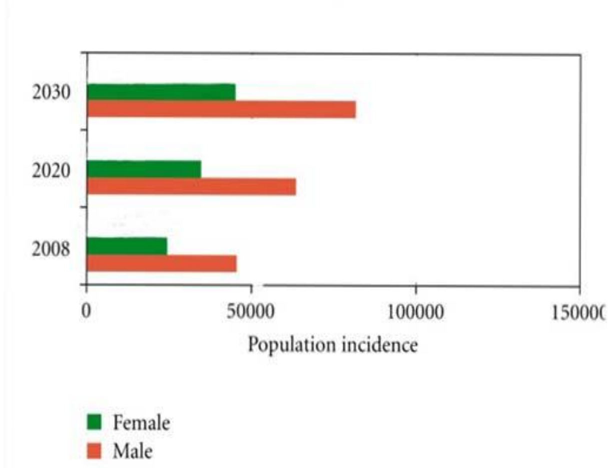


Locations of cancer registries in India.

Oral cancer affects 20 people out of every 100,000 people in India, making up around 30% of all cancer cases. In India, more than 5 persons pass away from oral cancer and the same amount from oropharynx and hypopharynx cancer every hour. Patients in remote locations have poor access to skilled professionals and relatively few health services. As a result, mouth cancer in its advanced stages is mostly to blame for the delay. The best likelihood of long-term survival is with early detection of oral cancer, which also has the potential to enhance treatment outcomes and lower the cost of healthcare. Due to a higher exposure to risk, oral cancer primarily affects those with lower socioeconomic position and those who live in rural areas. due to factors such as use of tobacco



Incidence and mortality or oral cancer in India



Incidence in India

Oral cancer affected 53842 men and 23161 women in India in 2012, according to the figures. Oral cancer is thought to be a disease that primarily affects elderly persons. However, the majority of occurrences of oral cancer occur between the ages of 50 and 70, however it can occasionally strike children as young as 10. Oral cancer incidence rises with age. The fifth decade of life is the most typical age. Men are more impacted than women across all age groups when taking gender into account. Men in India are affected by changes in behaviour and lifestyle habits two to four times more than women.

I. <u>Alcohol consumption</u>

Alcohol consumption is a significant mouth cancer risk factor. Risk increases with weekly alcohol use. Alcohol consumption increases the incidence by 49% among current users and by 90% among former drinkers, according to a prospective study conducted in India.

II. Region variation

Additionally, compared to wealthy folks, poor people have a higher age-specific death risk. Tamil Nadu and Kerala, two Indian states, have reasonably decent health outcomes. Future health advancements will be closely related to the country's economic success and collective commitment to fairness and the provision of universal health care. Pan parag, zarda, and other smokeless tobacco products are increasingly popular in north India, particularly in states like Uttar Pradesh. Oral cancer is very common in this area as a result of habit.

III. Use of Tobacco

According to estimates, between the ages of 15 and 49, 57% of males and 11% of women smoke. In more than 90% of OC cases, tobacco use is acknowledged. The use of smokeless tobacco, betel liquid, pan (pieces of Areca nut), processed or unprocessed tobacco, aqueous calcium hydroxide (slaked lime), and certain Areca nut pieces wrapped in Piper betel vine leaf are some of the tobacco consumption methods. Regardless of when they first started chewing tobacco, women who do so 10 or more times per day run a risk that is 9.2 times higher than that of non-tobacco users. In terms of oral dipping products, univariate analysis showed that the risk was 7.3 for consumption of gutka, 5.3 for consumption of chewing tobacco, and 4 for consumption of supari.

Oral cancer can also brought on by poor oral hygiene. More than 85% of patients with oral cancer in one research had bad oral hygiene . In India, the risk associated with poor oral hygiene is approximately 32% for males and 64% for women. Oral cancer was strongly connected with patients who had worn dentures for more than 15 years and who did not regularly see a dentist

While performing routine exams, healthcare professionals should be vigilant for the warning signs and symptoms of oral malignant and premalignant lesions. Recent research revealed variations in the frequency of oral cancer depending on parameters such as age, gender, aetiology, and anatomical sites of occurrence. The importance of prompt clinical evaluation when investigating suspected oral lesions was emphasised by these variables. In order to rule out additional primary malignancies in oral cancer patients, assessments of other possible sites like the oesophagus, larynx, hypopharynx, and lungs should be carried out in addition to the usual clinical and laboratory tests. Although a biopsy is regarded as a confirmatory diagnosis, it is important to validate and increase the clinical applicability of auxiliary advanced diagnostic techniques to detect early malignant tumours

6. CONCLUSION

In this paper, we evaluated the study on the use of several Al methods for the diagnosis of oral cancer disease. Al used an image processing algorithm and mobile image screening to play a key role in the identification of oral cancer. Using the structure of saliva, we can identify a person's pathological condition in addition to predicting oral cancer. Our review article can be expanded to include additional cancer types from different biomedical resources.