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Oral Cancer Detection Using Teachable Machine web Based Tool.

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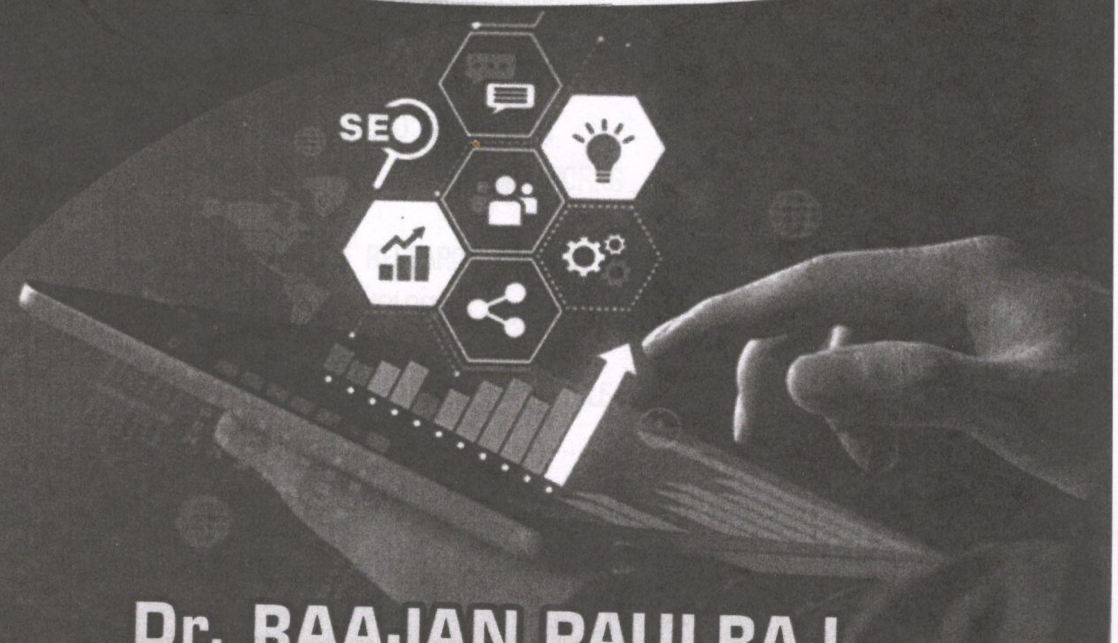

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ORAL CANCER DETECTION USING TEACHABLE MACHINE WEB BASED TOOL

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Abstract:

In the current age of the Fourth Industrial Revolution (4IR), a mass of research has been handled to make machines intelligent. It enables computers to learn from experience and understand the world in terms of a hierarchy of concepts. Pattern recognition offers vital appliance for healthcare analytics tasks. The models of machine learning and deep learning techniques applied to numerous healthcare tasks, such as risk prediction, deciphering disease progression, and patient subtyping, etc. Healthcare tasks offer plentiful challenges for pattern recognition. The heterogeneous, high-dimensional, non-linear, temporal, and distributed nature of the patient data complicates the traditional techniques. Such challenges inspire the pattern recognition domain to develop novel techniques to solve specific challenges in healthcare. The goal of this article is to showcase some of the latest and cutting-edge developments in pattern recognition for healthcare analytics in oral cancer.

Keywords: cancer, squamous cell carcinoma, pattern recognition, teachable machine learning.

I. Introduction

Pattern recognition is the science and art of giving names to the natural objects in the real world. Pattern recognition is an object description and classification method, it is also a mathematical, heuristic and inductive technique in executing the tasks like human being on computers. It's ultimate goal is to optimally extract patterns based on certain conditions and is to separate one class from the others [19]. The field of pattern recognition line up with technologies including regression, clustering, genetic algorithms, principal component analysis, trees and neural networks. The classical pattern recognition techniques rooted from statistics and decision theory, the machine learning model is commonly used to design practical systems. The process of recognition by computer is like that of human being. By pattern recognition, machines can recognize the patterns.

The Process of an automated pattern recognition system can be divided into two basic tasks: the description task constructs an attributes of an object using feature extraction techniques, and the classification task impute a group label to the object based on those attributes with a classifier. The description and classification tasks work together to decide the most accurate level for each unlabeled object examined by the pattern recognition system. [21].

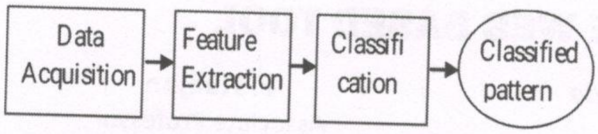

Figure1.1 Pattern recognition systems

The general processing activities of pattern recognition are Data acquisition, Feature Extraction and Classification [22]. Image preprocessing is a beneficial step in every pattern recognition system to revamp its performance.

DATA ACQUISITION

Data regarding objects are collected from the environment using similar kinds of sensor devices. Preprocessing is the stage where the input images are handled to get ready the data for succeeding activities in the description task or in the classification task. Few preprocessing tasks are noise reduction, filtering, encoding and histogram equalization. [21].

FEATURE EXTRACTION

Feature extraction is the kernel of a pattern recognition system. The process of feature extraction got up towards improving the raw data for classification purposes. The goal of feature extraction is to examine small number of features that are particularly distinguishing or informative for the classification process, and that are invariant to irrelevant transformations of the data. The pattern space is usually of high dimensionality, to reduce the aspect of the measurement space to a space suitable for the application of pattern classification techniques. Feature extraction can be view as a mapping, which portrays a pattern space into a feature space, and the capacity of the feature space has to be smaller than pattern space [23].

CLASSIFICATION

In order for each instance of a feature vector to be classified as belonging to one of N classes, the feature space must be divided into decision regions that correspond to the classes. In order to construct and model the classifier, classification involves the use of an inductive principle. Classifier parameter estimation requires the use of an optimization or learning technique. A classifier is used in the task to map a feature vector to a group. In order to assign identification to each unlabeled feature vector presented to the classifier, training is employed to generate the mapping from a collection of feature vectors. The methods for classification models are as follows:

1. Decision Trees
2. Synthetic neural networks
3. K-Nearest Neighbor
4. Simple Bayes.
5. Theorem of probabilities.

II. ORAL CANCER

The biggest health issue and the primary cause of cancer worldwide is oral cancer. When a tumour appears in a portion of the mouth, it is called oral cancer. It could be on the tongue's surface, the inside of the cheeks, the palate, the lips, or the gums. Additionally, tumours may form in the salivary glands, tonsils in the back of the mouth, and the portion of the throat that connects the mouth to the windpipe (pharynx). Oral cancer is tailored to the uncontrolled growth of cells which with time invades and affects the nearby organs whereas an understanding of the type of oral cancer will help in carrying out proper diagnosis and treatment. Risk factors for oral cancer include smoking or spit (chewing) tobacco and excessive use of alcohol, infection with HPV and sun exposure may develop oral cancer.

Squamous cell carcinomas, commonly known as squamous cell cancers, make up the majority of oral cancers. Squamous cells, which are flat, thin cells that make up the lining of the mouth and throat, are where these malignancies begin.

2.1 ORAL CANCER SCREENING AND DIAGNOSIS

Early diagnosis is very important to avoid oral cancer. Screening tests are performed regularly on people who look healthy and are not suspected of having oral cancer. Screening reduces mortality by oral detection, called early detection of oral cancer. If the results of the screening test are abnormal, a diagnostic test is needed to determine if the patient has cancer. Using screening techniques such as computer tomography (CT), positron emission tomography (PET), magnetic resonance imaging (MRI), and histopathology, we suspect that a person has oral cancer. .. However, the only way to confirm that a person has oral cancer is to perform a diagnostic test such as FNA (Fine Needle Aspiration) or histopathology. These tests remove suspicious tissue found during screening and look under a microscope for cancer.

2.2 ORAL CANCER DIAGNOSTIC TECHNIQUES

The demand for oral cancer diagnostic techniques has recently increased to screen for malignant parts of oral lesions. There are several diagnostic tools on the market today. Among them are the most commonly used techniques [25].

- Histopathology is considered the gold standard test for cancer diagnosis. The effectiveness of the results depends on several factors, including the location of the suspicious area and the number of biopsy samples taken from the malignant and normal tissue areas.

- Vital stain techniques are used to clinically highlight the malignant areas of oral lesions. Taking biopsy samples can be useful, but unfortunately these techniques are unreliable.
- Brush biopsy techniques use a small nylon brush to collect cytological samples and scan and analyze them with computer software to detect if each cell is cancerous.
- In general, abnormalities at the cellular and molecular levels of tissue are invisible to the human eye. It can only be observed by passing light through the tissue and detecting changes in the optical spectrum.

2.3 IMAGING TECHNIQUES

Oral cancer is diagnosed using a number of cutting-edge imaging techniques. The most often employed scanning methods among these are CT, MRI, and PET [26].

Computed tomography (CT) scan: In order to find the cancerous tumour and evaluate whether it has spread to other parts of the body, a CT scan employs x-ray radiation and a computer to create images of the body. The CT scan is a commonly available and financially more affordable treatment, making it a standard imaging method for the detection of head and neck malignancies. However, it has been found that a CT scan cannot detect lesions in the early stages. CT scans can only reveal small, early-stage tumours in the buccal cavity after being enhanced with an intravenous contrast agent.

Magnetic resonance imaging (MRI): MRI, or magnetic resonance imaging, offers information on the structures in the mouth cavity and its surrounding areas. The MRI's ability to distinguish between soft and hard tissues helps in determining the tumor's lymphadenopathy, invasion depth, and local and regional spread. Due to its extremely high contrast resolution and multiplanar views, MRI is a reliable method for detecting the spread of oral cancer to the surrounding soft tissues. As a result, MRI is essential for the pre-treatment evaluation of advanced oropharyngeal and oral cancer. MRI helps in identifying the origin, location, and borders of lesions as well.

Positron emission tomography (PET) scan : The PET scan is used to assess whether tumour cells have migrated to the lymph nodes or other bodily regions. Gamma rays released by the positron decays are scanned after a radioactive dye has been ingested or infused. The staging of the lymph nodes is determined using this precise procedure. If nodes are found apart from the afflicted region, it does not suggest a change in the treatment strategy even if additional lymph node metastases is found.

III. TEACHABLE MACHINE

A web-based programme that quickly and readily produces models is known as a teachable machine. Pose, voice, and picture recognition are its three functions. Its adaptability is a plus. It can instruct a model in how to categorise pictures or postures using pictures or a live webcam. It is cost-free and ideal for students. A web app, an Android app, or any other platform can be integrated with the model that is produced by Teachable Machine. Teachable Machine trains and runs the models you create in your web browser using TensorFlow. js, a Javascript machine learning toolkit.

The engine gathers the dataset from the user, trains on the supplied data, and then makes a prediction. This model can also be downloaded, as was previously noted. With Teachable Machine, users may build quick and efficient browser-based algorithms that can: Identify patterns in photos and audio; Identify stances or motions;

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The Kaggle Dataset, which included 1224 oral histopathology pictures (290 non-cancerous and 934 malignant) from 230 patients, provided the Histopathologic Image. Instances of both classes from the dataset are shown in Figure 4.1. The images were obtained using a Leica ICC50 HD microscope at two different magnifications (100x and 400x) from tissue slides that had been stained with hematoxylin and eosin (H&E). 439 photos of malignant epithelium and 89 images of normal epithelium were magnified by 100 times each, while 201 normal images and 495 OSCC images were magnified by 400 times each (Figure 4.2).

Table 4.1 Details of dataset

S.NO	DATASET NAME	DATASET LINK
1	Histopathologic Oral Cancer Detection	https://www.kaggle.com/ashenafifasilkebede/dataset

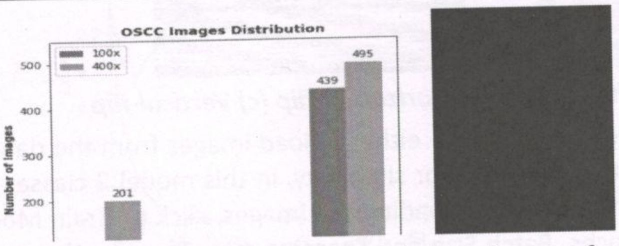

Figure 4.1: Vignettes of H&E stained oral histopathology images from the Oral Cancer dataset capturing normal epithelium (a) and cancerous epithelium(b)

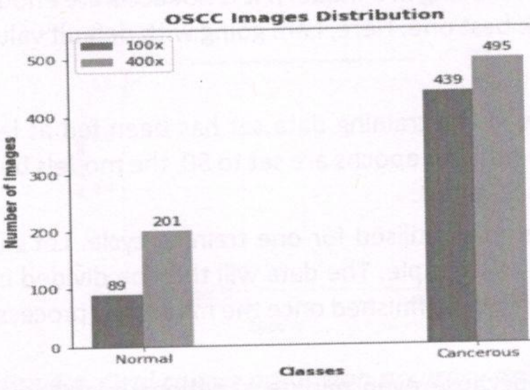

Figure 4.2. Distribution of images in the dataset.

The Normal and Cancerous class contains 290 and 934 images, respectively. The images are in two different magnifications — 100x (89 Normal, 439 Cancerous) and 400x (201 Normal, 495 Cancerous)

4.1. Data Augmentation

The dataset's photos were lacking and their classes were unbalanced. When ML models are trained on a limited dataset, over-fitting occurs, which drastically reduces the models' capacity to generalise. The models perform poorly in terms of prediction when the data is unbalanced, especially for the minority class. used strategies for data augmentation to resolve these problems. Two folds were added to the non-cancerous photos in the minority class using geometric alterations such the horizontal-flip and vertical-flip (Figure 4.3). The flipped images are invariant because pathologists can quickly analyse the images from various perspectives. Similar to this, by enhancing the photos during training, the data's overall size was enhanced.

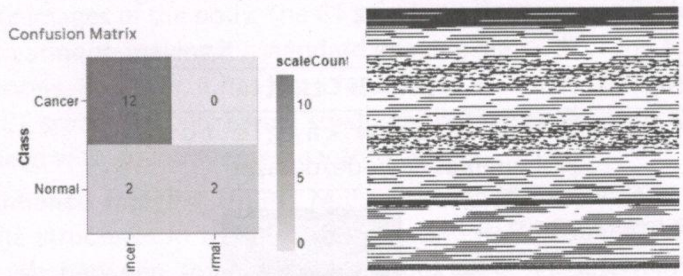

Figure 4.3: (a) Original image (b) Horizontal-flip (c) Vertical-flip

In the web based tool There are two options – either upload images from the dataset or use the live camera to capture the images. For simplicity, in this model 2 classes are created such as normal and cancerous. After uploading the images, click on Train Model. It will show different options – Epochs, Batch Size and Learning rate. To make the model more efficient, it's important to play with them and find out at which values model gives the highest accuracy. Of course, there is no meaning in a model if it is not accurate enough. We can change their values and find out the best one. Here, I am going with default values.

4.2 System Performance Measures

Epochs: During an epoch, every sample in the training data set has been fed at least once through the training model. For instance, if the epochs are set to 50, the models being trained will go over the full training dataset 50 times.

Batch Size: A batch is a collection of samples utilised for one training cycle. Let's use an 80 image sample and a 15 batch size as an example. The data will then be divided into 80/16=5 batches as a result. Exact one epoch will be finished once the model has processed all 5 batches.

Be cautious when adjusting this value because even minute variations might have a significant impact on how quickly your model picks up new information.

Precision: - The easiest performance metric to understand is accuracy, which is just the proportion of properly predicted observations to all observations.

Table 4.2 Details of accuracy per class

Accuracy per class

CLASS	ACCURACY	# SAMPLES
Cancer	1.00	12
Normal	0.50	4

Loss:- A numerical value that represents how far off the mark the model's predictions are is referred to as "loss." It's a type of payback for a bad forecast. If the loss value is 0, the model is perfect; otherwise, it is not.

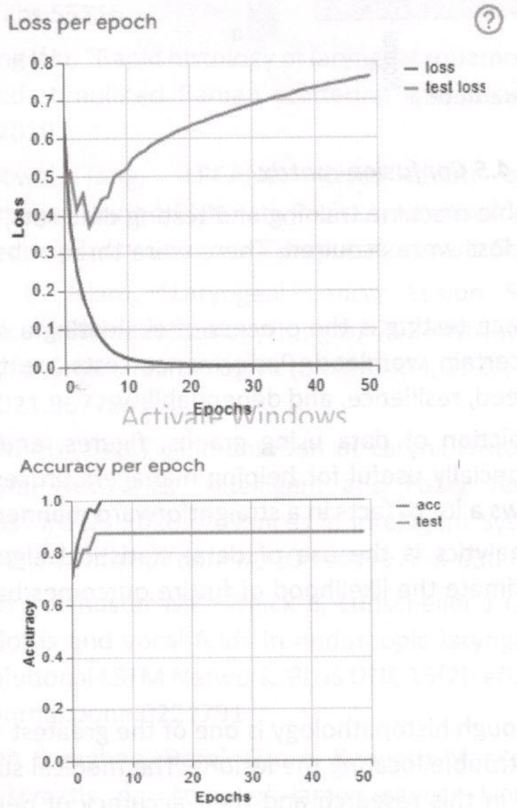

Figure 4.4. Oral cancer prediction accuracy and loss with respect to iteration during training.

The teachable machine divides samples into training and test buckets. The model is trained using 85% of the samples. 15% of the samples are never used to train the model; instead, they are utilised to test the model's performance on brand-new, untested data after the model has been trained on the training samples.

Figure 4.5 demonstrates that the suggested model accurately predicted 12 samples with oral cancer and 2 samples that are normal. Additionally, the suggested model incorrectly identified two normal samples as cancerous.

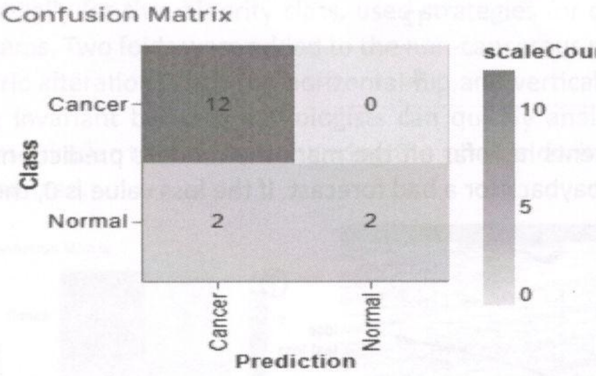

Figure 4.5 Confusion matrix

After applying processing to teachable machine training and testing data sets, various sets of findings based on accuracy and loss were acquired. There were three subsections within it:

Performance evaluations: Performance testing is the process of evaluating a system's responsiveness and stability under a certain workload. Performance tests are typically conducted to assess application size, speed, resilience, and dependability.

Graphical analysis: A graphical depiction of data using graphs, figures, and charts is known as a graphic analysis. It is especially useful for helping managers process large amounts of data. This kind of study shows a lot of facts in a straightforward manner.

Predictive analytics: - Predictive analytics is the use of data, statistical algorithms, and machine learning techniques to estimate the likelihood of future outcomes based on historical data.

III. Conclusion

Oral cancer prevalence is rising. Although histopathology is one of the greatest ways to find oral cancer, pathologists may have trouble locating the lesions. The medical staff may benefit from the procedures described in this research and their accuracy of detection. Images are taken and a number of operations are carried out in this study to categorise them as normal or abnormal.

Following are some of the research's potential future improvements:

Future research on the features extracted from oral cancer data is required to produce better and more accurate outcomes.

Using optimization approaches, adding a fuzzy hierarchical classifier to neural networks.

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