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Oral Cancer Detection using Deep Learning

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***Abstract*—The rising frequency of oral cancer and its devastating impact on public health necessitate the development of more accurate methods for early detection and diagnosis. This study presents a groundbreaking approach that utilizes convolutional neural networks (CNN) to improve the precision of medical image-based oral cancer diagnosis. Our meticulously crafted model, fine-tuned and optimized for oral cancer characteristics through transfer learning with pre-trained models, achieves an impressive accuracy rate of 81%. This study underscores the potential of deep learning methods, particularly CNNs, as highly effective tools for achieving precise and early detection of oral cancer. The results unequivocally demonstrate the efficacy of our model in accurately distinguishing between different oral cancer conditions, thereby paving the way for improved diagnostic accuracy, and contributing to better patient outcomes. Overall, our research significantly advances the evolving landscape of medical image analysis and reinforces the indispensable role of advanced technologies in addressing critical healthcare challenges.**

***Index Terms*— Oral cancer, image processing, convolutional neural networks, and deep learning.**

I. Introduction

Oral cancer is the general term for any kind of cancer that develops in the oral cavity of the mouth. Oral cancer or cancer of the oral cavity are other names for cancer of the mouth. It can appear on the tongue, lips, knees, cheek lining, and floor of the mouth (below the tongue). The term "head and neck cancers" refers to a group of diseases that includes oral cancer. Treatment for head and neck malignancies is frequently the same for oral cancer as well. Half of all incidences of oral cancer occur in South Asia, and two thirds occur in low- and middle-income nations globally. The two biggest risk factors for oral cancer are heavy drinking and tobacco use. Throughout Southeast and South Asia, the most significant In this work, various DL categories for the provision and discussion of early detection of oral cancer. The promise of machine learning algorithms for diagnosing and predicting oral cancer has been demonstrated by earlier research. Oral cancer cells may be reliably detected and classified using Convolutional Neural Networks (CNN). In addition to the input and output layers, CNNs also include fully linked, convolution, and maximum pooling layers. These layers help CNNs extract abstract features from incoming data that is based on pictures. It is imperative to discover oral squamous cell carcinoma (OSCC) as soon as possible to reduce treatment adverse effects and the mouth cancer fatality rate.

II. Literature Survey

In this paper, an automatic CNN algorithm is used to detect oral cancer using image processing methods. In this test result, background and bony parts are very efficiently separated, which helps doctors throughout the

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diagnosis and detection process automatically of oral cancer[1]. Artificial intelligence used in the diagnosis of mouth cancer has been emphasized due to its capacity to raise the precision and effectiveness of diagnostic instruments.This could lead to faster and more accurate detection of oral cancer, improving patient outcomes[2]. They find Rep tree and random tree are best models to detect oral cancer. Further it can be improved by using MATLAB to classify different datasets[3]. This suggests that the model considers different sources of information, including risk factors, systemic diseases, and clinicopathological data. This comprehensive approach can lead to a more accurate forecast[4]. Our cost estimates provide comprehensive information that helps decision makers plan medical payments more effectively. In a country with large affordability differences, these results are important for the development of an illness-oriented, objective approach to treating oral cancer. In addition, the treatments and cost model created in this investigation can complement the existing proof and act as an example for more malignancies in different countries in different settings[5]. Since current techniques are not yet prepared for use as diagnostic instruments in clinical settings, much work is needed and it can be expected that simple, rapid, Clinical diagnostic systems that are affordable and portable may be accessible soon [6]. Based on the findings of this study, it can be taught to community health workers in low-and middle-income countries to detect oral cancer [7]. The treatment of malignant tumors of the oral cavity depends mainly on the location and size of the tumor and the possibility of preserving the patient's organs. Surgery and radiation therapy are advised when oral cancer initially manifests[8]. Oral cancer ranks tenth among women's diseases and sixth among men's. , and it burdens healthcare providers and the public, on the other hand, many of its risk factors, such as smoking and hookah, are controllable. , including screening and diagnosis early in the health system, and training programs are recommended[9]. Although the CNN method is a good and powerful tool, but compared to the classic SVM and Naive Bayes methods. This work described operations performed on input images to identify their phase as normal or abnormal[10]. The project showed that studies on Early pharyngeal and oral cancer detection can be successfully conducted in cooperation with private practice dentists. The gathering clinical and epidemiological information on the early identification of lesions in the oral mucosa in daily circumstances demonstratedto be both possible and successful[11]. Probabilistic neural networks have the highest classification sensitivity, specificity and accuracy and are the best in terms of geometrical mean specificity and sensitivity making it a solid model.[12] According to a CEA study, mass screening and high risk screening have fewer cases and fewer deaths from oral cancer than no screening.[13] High-risk screening strategies were found to be more cost effective than mass screening at various intervals.[14] ABC performs well in the segmentation phase because it has a higher recognition accuracy than other approaches.[14] CNN, ABC, FPSO are three approaches used to develop a novel method to detect mouth cancer within CT images Artificial intelligence offers the opportunity to develop novel methods in combination with established strategies to improve the precision of OC & OPMD identification, and to use historical data to predict the development of cancerous and precancerous lesions[15].

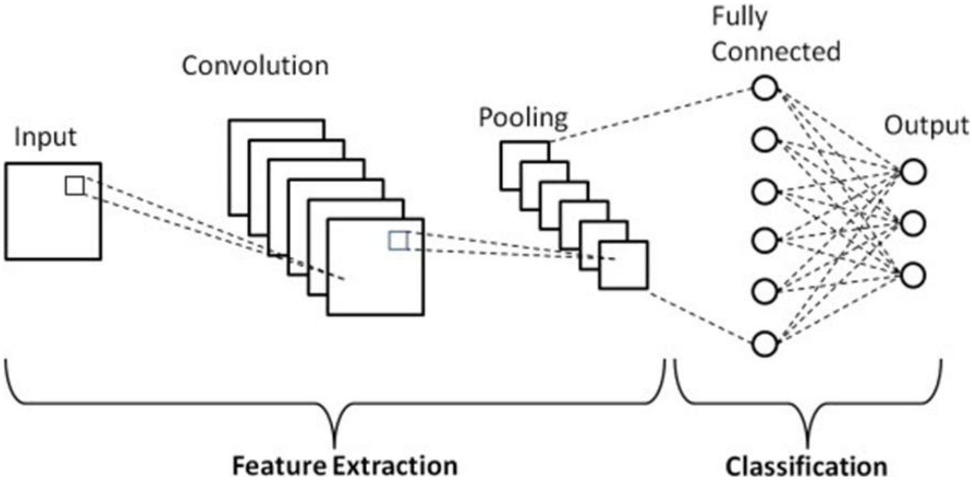
A. Dataset Information

The study comprises of Oral cancer image dataset which contains some cancer images and some non-cancer images. In the dataset 111 images are cancerous and 130 are non-cancerous. In those 111 cancer images 77 is taken for training, 17 for validation, and 17 for testing. In 130 images of non-cancerous images 91 images is taken for training , 19 for validation, and 20 for testing. In this research, detection of oral cancer is addressed. The study was completed with manually annotated data collected from various social media sources. These sources include popular platforms known for user-generated content, noting the diversity and representation of the dataset. This additional data was carefully added to increase the diversity and size of the dataset providing a comprehensive analysis covering a wide range of expressions and popular languages in social media conversations.Using a combination of precompiled resources and manually annotated data, the study aims to build a robust model.

B. Proposed Method

The proposed method utilizes Convolutional Neural Networks for Feature Extraction. The CNN is responsible for the automatic feature extraction from oral cancer images and subsequent classification. The convolutional layers learn hierarchical representations, and the fully connected layers make predictions based on these learned features. Convolutional layers are used to apply a series of convolutional filters to the input images. These filters are designed to detect various features, patterns, or textures in the input images. A collection of feature maps is what the convolutional layers produce. Each feature map highlights different aspects of the input images based on the learned filters. After the convolutional layers, max-pooling is applied to down sample the feature maps.

Max-pooling extracts the most important information from each local region of the feature maps. This aids in reducing the spatial dimensions and retaining salient features.



The Conv2D layer performs a 2D convolution applied on the source data. A convolution kernel is produced by that layer thatis joined with the input to the layer over one spatial (or temporal) dimension to produce a tensor of results. If the activation isnot set to None, it will also be implemented on the outputs. those at the beginning of the network architecture, which is more akin to the input image itself decrease your familiarity with convolutional filters, whereas layers located further down the network—that is, nearer the output predictions—learn more about filters. Compared to earlier iterations, intermediate Conv2D layers pick up on more filters, but less than layers closer to the output. The following is the formula for a convolution operationin a neural network:

Bias(k)+∑l=0L−1(∑m=0M−1∑n=0N−1) is the output(i,j,k) ----------(i)

input(i+m,j+n,l)×Kernel(m,n,l,k))------------- (ii)

Rectified Linear Unit (ReLU) is a non-linear activation function that is commonly used in the hidden layers of convolutional neural networks (CNNs). This is an additional step of the CNN convolution operation and aims to increase the non-linearity of the images.The ReLU layer is activated only when the node's input exceeds a certain amount. This is different from the tanhand sigmoid activation functions, which learn to evaluate the null result. ReLU adds nonlinearity by zeroing out all negative values.It facilitates the network's discovery of intricate correlations and patterns in the data. Every value in the input tensor receives an element-by-element application of the activation function. The definition of ReLU, an activation function, is:

ReLU(x)=max(0,x)----------------(iii)

Sigmoid ranges input values between 0 and 1. It is frequently utilized in binary classification models' output layer, where it transforms the network's raw output into probabilities. Making sure the result is within a legitimate probability range is aided by it. The output is an input for the next level after being passed through an activation function with the weighted sum of the inputs. The output of this unit will always be between 0 and 1 if a neuron's activation function is a sigmoid curve. Since the sigmoid is a non-linear function, the unit's output would be non linear. It would be a linear function of the weighted sum of the inputs. A neuron with a sigmoid function as its activation function is called a sigmoid unit.

Sigmoid(x)=1/1+e^-x ----------------- (iv)

These functions are crucial components of neural networks, contributing to the model's ability to learn complex representations and make predictions. The Conv2D layer extracts features, ReLU introduces non-linearity, and Sigmoid provides a suitable output.

CNN Channel
The CNN channel applies convolutional filters to the embedded input to extract local feature maps, followed by a maxpooling operation:

mi = ReLU(Conv1D(ei)) ----------------(v)
mi = MaxPooling1D(mi)---------------- (vi)

where mi is the feature map that was retrieved at location I following the application of max pooling, ReLU activation, and convolutional operation.

III. ARCHITECTURE DIAGRAM

An architectural schematic of the suggested approach is as follows:
Input Layer:
There is no specific code for this, but it is presumed that the input data has the shape (256, 256, 3), which stands for images with three RGB color channels and 256 x 256 pixels.
Convolutional Layer 1:
Conv2D(input_shape=(256, 256, 3); activation='relu'; filters=32; kernel_size=(3, 3).)
Applies to the input image 32 3x3 convolutional filters. Use the activation function of the Rectified Linear Unit (ReLU).Anticipates receiving an input shape of (256, 256, 3).
Layer 2 Convolution:
Conv2D(activation='relu', kernel_size=(3, 3); filters=32) Incorporates a 32-filter convolutional layer with ReLU activation.
After the first layer, there's no need to specify the input shape because Keras infers it automatically. Max First Layer of Pooling:
MaxPool2D(pool_size=(2, 2)) uses a 2x2 pool size and max-pooling to downsample the spatial dimensions. Layer 3 Convolution:
Conv2D(activation='relu', kernel_size=(3, 3) filters=64) adds a 64-filter layer to allow for more intricate feature extraction.
Max Layer 2 Pooling:
MaxPool2D(pool_size=(2, 2))
For even more downsampling, add another max-pooling layer.Layer 4 Convolution:
Conv2D(activation='relu', kernel_size=(3, 3), filters=128) adds a layer for higher-level feature extraction that has 128 filters.Layer 3 Max Pooling:
MaxPool2D(pool_size=(2, 2)) One more layer of max-pooling.Layer of Dropout:
Dropout (rate=0.25)
Introduces a 25% dropout rate to avoid overfitting.Layer Flattening:
Flatten() creates a vector representation of the multi-dimensional data that is fed into the dense layers. Dense Layer 1:
Dense (activation='relu', units=64) A layer with 64 units (neurons) with ReLU activation that is fully linked. Layer 2 Dropout:
Dropout (rate = 0.25). An additional dropout layer to reduce overfitting even further. Layer 2 Dense (Output Layer):
Dense (activation='sigmoid', units=1)
The last dense layer for binary classification (e.g., presence or absence of a feature) has one unit and sigmoid activation. Model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']) is the compilation method.
Creates the model accurately, which serves as the binary crossentropy loss function, the Adam optimizer, and the evaluationmetric. Summary of the Model:
model.summary()
Provides an overview of the model architecture, indicating the kind and dimensions of every layer as well as the overall quantityof parameters.

IV. RESULTS

This process may take less time compared to the existing system.When compared to the existing the dataset with images cangive best result when CNN to detect the oral cancer.

V. CONCLUSIONS

This paper discusses the collection and labelling of pictures of the mouth and shows the results for automating early oral cancerdetection. The results of this helps us to ease identification of oral cancer with the help of images. In this we use CNN algorithm for detection of Oral cancer. The **CNN** model should be selected based on the

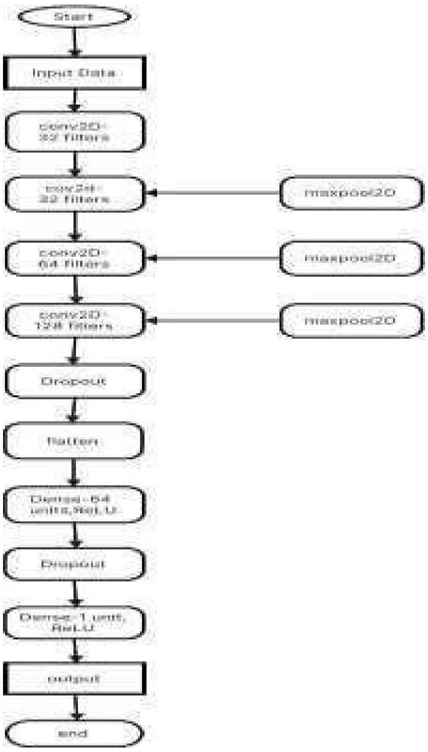
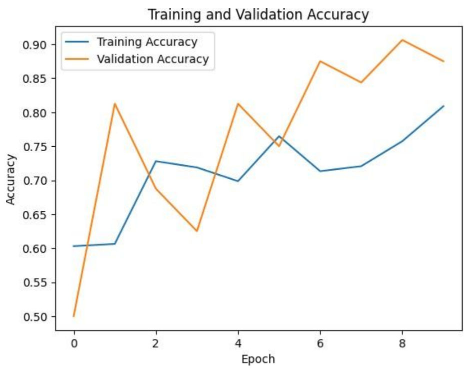


Fig-1:Flowchart diagram



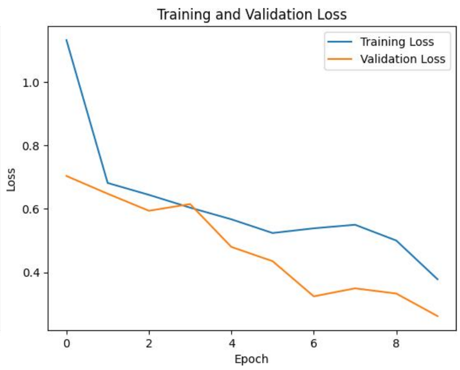


Fig-2: Training and vadlidation accuracy

Fig-3: Training and validation Loss

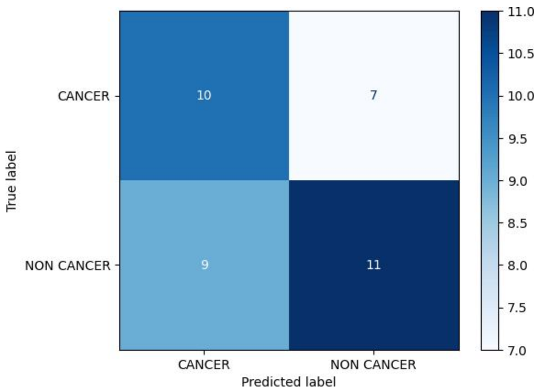


Fig-4: Confusion matrix

specific characteristics of the dataset, considering the interpretability of the results, and aiming for a predictive accuracy of **89.19%**.

FUTURE SCOPE

For Future work, Testing the past data and gathering information about the oral cancer , updating the data will result in increasing the accuracy and steps to prevention . The images of symptoms of oral cancer should aslo be updated regularly to get the efficient and required output.

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