IDENTIFYING AND CLASSIFYING ORAL CANCER BASED ON DEEP TRANSFER LEARNING

Nivetha S[2], Hariraaghava R K[3], Selvaraj M[4], Pandiyan M[4]

[1,2]*Student, Department of Computer Science and Engineering, Bannari Amman Institute of Technology, Tamilnadu, India*

[3]*Student, Department of Mechatronics, Bannari Amman Institute of Technology, Tamilnadu, India*

[4]*Assistant professor, Department of Information Science and Engineering, Bannari Amman Institute of Technology, Tamilnadu, India*

ABSTRACT

The "head and neck cancers" that occur most often worldwide are oral cancers. Oral cancer is a common, intricate, and very dangerous type of cancer. In India, oral malignant growth positions seventh among all tumors, with 130,000 fatalities annually. The tumor has an impact on the tonsils, salivary glands, face, mouth, and neck. The majority of oral cancer cases are only identified in advanced stages due to an absence of public mindfulness. In this specific circumstance, computerized reasoning (artificial intelligence) and AI (ML) models are utilized since it is critical to distinguish sicknesses from the beginning for improved results. The ongoing work presents the Oral Disease recognition and Characterization Model (AIDTL-OCCM), which is controlled by man-made reasoning and profound exchange learning. The proposed AIDTL-OCCM model's main objective is to identify oral cancer utilizing AI and image processing methods. The AIDTL-OCCM model under consideration uses a fuzzy-based contrast enhancing method. Then, a suitable set of deep features is produced using the densely-connected networks (DenseNet-169) model. Additionally, the Autoencoder (AE) model of the Chimp Optimization Algorithm (COA) is employed to identify and classify oral cancer. To be able to to choose the best AE model parameters, COA is also used. Benchmark datasets were used as the basis for a wide range of experimental investigations, and the outcomes were examined from a number of angles. With a maximum accuracy of 90.08%, the results of the thorough experimental investigation demonstrated the AIDTL-OCCM model's superior performance over other methods.

Keywords: *Oral cancer detection, Transfer learning, Image classification, CNN, Artificial Intelligence.*

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1. INTRODUCTION

One of the most prevalent illnesses in the world is oral cancer due to its high mortality rate, high morbidity rate, and late diagnosis. Two important risk factors for oral lesions are smoking and heavy drinking. According to reports, oral cancer becomes uncontrolled when cells that feed damaged surrounding tissues expand. Less dead cells in the oral mucosa, which is characterized by ulcers, may be an early symptom of oral cancer. When metabolism takes place, dead cells can be discovered throughout the body or in specific areas of the area. The survival rate is decreased because more than two thirds of oral lesions develop later. It is costly to manage lesions, especially later on. The features of the lesion are not defined by late discovery since oral lesions are commonly accompanied with visible lesions known as oral potentially malignant disorders (OPMD). Clinical Oral Examination (COE) tests are used by dental experts to diagnose this during normal screening. In order to further treat the patient's condition and establish the diagnosis, a professional examination is advised when an uncertain malignancy is identified.

Previous Indian study shows that screening and earlier diagnosis have decreased death rates and staged disease in alcohol and tobacco users. Since there is a constant shortage of healthcare experts and resources, oral lesion screening programs must be aggressive, economical, and effective. Given this context, telemedicine, a sort of technology, may be a practical means of making an early diagnosis. Deep learning (DL) and computer vision (CV) breakthroughs have made it is technically feasible to develop a tool that can autonomously scan a person's oral cavity and provide feedback to health care providers during patient examinations as well as to the patient for self-examination. Early studies on the using imaging techniques including optical coherence tomography, auto fluorescence imaging, and hyperspectral imaging was the main emphasis of image-based automated diagnostics for oral cancer. Virtually all prior research was focused on the identification of particular types of oral lesions, with the exception of one or two studies that made use of white-light photographic images.

The identifying and classifying oral cancer based on deep transfer learning model (AIDTL-OCCM) was developed in the current work using AI. The main objective of the proposed AIDTL-OCCM model is to identify oral cancer utilizing AI and image processing methods. The proposed AIDTL-OCCM model first uses a fuzzy-based contrast enhancement approach to complete data pre-processing. It also makes use of the densely-connected networks (DenseNet-169) model to provide a useful collection of properties. Oral cancer detection and classification are done using the Chimp Optimization Algorithm (COA) and Auto encoder (AE) model. The best AE model parameters are chosen using COA, which is also used to identify other important factors. On benchmark datasets, a broad variety of experimental studies were carried out, and the outcomes were examined from a number of angles.

2. LITERATURE SURVEY

In the literature, a unique technique for merging the bounding box annotation from several doctors was presented. To construct automated systems with this challenging goal in mind, Deep Neural Network (DNN) was also used, resulting in the formation of challenging patterns. Due to the use of the main data obtained in this case, the automatic identification and categorization of oral lesions was considered using two DL-based CV techniques. The patient's hyperspectral image was taken into consideration when Jeyaraj et al. developed a DL approach for computer-aided and automated oral cancer detection. Classifier sensitivity, accuracy, and specificity were compared to those of other methodologies in order to validate the effectiveness of the provided partitioned DL approach based on regression.

To solve the challenges involved in the automated identification of oral diseases, Lin et al. suggested an efficient system for mobile image analysis under the supervision of DL. It could be completed as a retrospective analysis. The approach for acquiring centered-rule images of the oral cavity in this work is straightforward but effective. Then, using this technique, a medium-sized oral data set with five different disease types is produced, and a resampling strategy is anticipated to decrease the impact of the picture variability in handheld smartphone cameras. In the end, a new DL network (HRNet) was developed to evaluate the viability of the proposed approach for oral cancer detection.

3. DEEP TRANSFER LEARNING

Deep transfer learning is a machine learning approach that uses the knowledge learned from one specialized assignment to improve the performance of an unrelated activity. This approach proves particularly advantageous when confronting a dearth of annotated data for the intended target task. It hinges on the fundamental notion that the lower tiers of a neural network, like the convolutional layers, acquire generic features that offer utility across a broad spectrum of tasks. Simultaneously, the upper layers are primed to grasp task-specific intricacies. This ingenious strategy empowers the model to harness the wealth of information gleaned from a cognate task boasting a more abundant dataset, thereby fortifying its capacity to excel in the designated mission. Deep transfer learning is a powerful method that allows a model to use the information it has learned from one job to better execute another one that is related, especially when labelled data is hard to come by. Natural language processing and computer vision are two fields where it is often employed, and it has shown to produce cutting-edge results in a range of applications.

3.1. Main Approaches Of Using Deep Transfer Learning

3.1.1. Fine-Tuning

Applying or making use of transfer learning involves fine-tuning. In particular, fine-tuning is the act of refining or tweaking a model that has previously been trained to perform one specific job in order to have it execute a second task that is comparable.

3.1.2. Feature Extraction

Deep learning feature extraction is more accurate and outcome-driven. In order to solve an issue using machine learning techniques, it must first be divided into smaller, subsequent problems that are then combined at the end.

3.1.3. Domain Adaptation

Using the information the model has gained from another similar domain with sufficient labelled data, a technique known as "domain adaptation" may be used to improve a model's performance on a target domain with inadequate annotated data. Adaptation to the domain. Essentially, domain adaptation is a subset of transfer learning.

3.1.4. Multitask Learning

Numerous transfer learning mechanisms are included in multi-task learning. Its fundamental goal is to train a single model to handle several problems. Although it occasionally can be done sequentially, this is often done in parallel.

3.1.5. Knowledge Distillation

By transferring information from big, complicated models to smaller, simpler models, knowledge distillation is a potent strategy for boosting tiny models' performance. The applications it has been effective in include speech recognition, computer vision, and natural language processing, to name just a few.

3.1.6. Transfer Learning With Meta-Learning

Meta refers specifically to training many tasks, and transfer is accomplished by learning the scaling and shifting DNN weight functions for each task. In addition, we provide the hard task (HT) meta-batch scheme as a productive MTL learning program.

3.1.7. Transfer Learning With Gans

In machine learning, GANs are used to conduct unsupervised learning tasks. Two models make up the system, and it automatically finds and learns the patterns in the input data. Generator and Discriminator are the two models' names. They compete with one another to examine, identify, and reproduce the changes present in a dataset.

4. PROPOSED MODEL

The ongoing research aims to improve the identification and categorization of oral cancer. has created a unique AIDTL-OCCM model. Fuzzy-enabled preprocessing, feature extraction using DenseNet-169, classification using AE, and parameter optimization using COA are some of the processes the described AIDTL-OCCM approach goes through. The best AE model parameters are chosen using COA, which is also used to identify other important factors.

4.1. Contrast Enhancement Using A Fuzzy Basis

Histogram Equalization (HE) is used to increase the contrast level of photographs. In comparison to the input photos, extremely complex image divergence is produced by fuzzy enabled image pre-processing. Due to the difficulty in understanding high resolution medical pictures, image preprocessing is done to enhance the image quality. The conversion of color photos into grayscale images is a significant advantage of this paradigm. It uses the fuzzy-based Contrast Limited Adaptive Histogram Equalization (CLAHE) model to make the image easy to see.

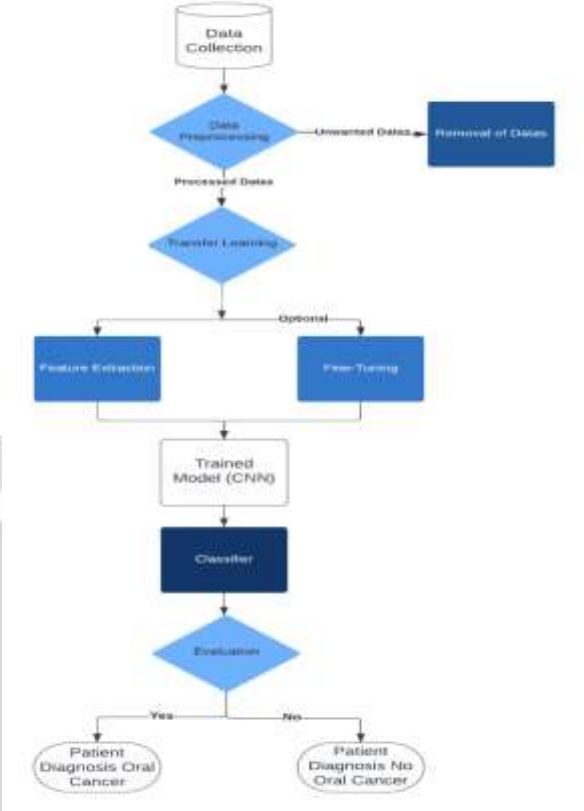

Fig-1: Methodology proposed

4.2. Feature Extraction Based On Dense-169

The previously altered images are then fed into the DenseNet-169 model, which generates a set of feature vectors. In the process of recognizing images, DCNN is a highly effective framework since it has access to particular pooling and convolution layer types. However, as the system becomes more complex, the amount of input data or gradient that must pass through each layer increasingly decreases, opening up access to the layer below it in the network. DenseNet ingeniously addresses the gradient vanishing problem by establishing direct connections between layers of the same feature size. This unique architectural feature ensures the seamless flow of gradients during training. One prominent advantage of employing the DenseNet model as a feature extractor lies in its ability to unearth richer and more comprehensive general features through meticulous layer-to-layer scrutiny. The DenseNet-169 model kicks off with an initial layer comprising pooling and convolutional operations, succeeded by three transitional layers, culminating in four densely connected blocks.

Stride 2 and 3x3 max pooling are used in the first convolution layer to achieve 7x7 convolution. The network then consists of three sets of dense blocks, each of which has a layer of change. By shifting a direct link from one layer to another, the DenseNet creates its dense connections. The gradient flow across the network is improved since the last layer receives the feature maps from every layer before it. This requires joining together the feature maps from the previous layer, which cannot be done unless each feature map has the same size. On the other hand, a convolution neural network is primarily concerned with down sampling the feature-map's dimensions. Several tightly linked blocks make up the DenseNet model, as was already explained. Described as a transition layer, this layer sits in between these thick blocks. A layer of batch normalization, a layer of 1x1 convolution with a stride of 2, and a layer of average pooling with a 2x2 size are included in each transition layer. There are four dense blocks, as was indicated previously, and each one is made up of two convolutional layers of 1x1 and 3x3 sizes. DenseNet169's pre-trained model, which was built on ImageNet, has 4 dense blocks that are each 6 by 12 by 32 pixels in size. The last classification layer employs global average pooling of 7x7 in contrast to the final FC layer, which employs the activation "softmax".

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 32)	896
conv2d_1 (Conv2D)	(None, 252, 252, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 126, 126, 32)	0
conv2d_2 (Conv2D)	(None, 124, 124, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_3 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
dropout (Dropout)	(None, 30, 30, 128)	0
flatten (Flatten)	(None, 115200)	0
dense (Dense)	(None, 64)	7372864
dropout_1 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total params: 7,475,425
Trainable params: 7,475,425

Fig-2: DenseNet model Layers

4.3. AE-Based Classification

To correctly identify the class labels for test photographs, the classification process makes use of the AE model. The components of AE are an activation function, a reconstruction layer of the d unit, a concealed layer of the h unit, and an activation function. In the training phase, the input $x\varepsilon R^d$ is first mapped to a hidden state, creating the latent activity, $y\varepsilon R^h$. The network, also known as an "encoder", corresponds to the process described in the boxed area. After that, y is translated into an output layer called "reconstruction" that is the same size as the input layer using a "decoder". $Z\varepsilon R^d$ represents the reconstructing value. While the reconstructed layer and parameter are removed during network training, the hidden node's learned features can be used for classification or as a source for future deep features by high layers.

4.4. COA-Based Parameter Optimization

COA is used during the parameter optimization process to determine the AE model's parameter values. In the case of irregular irradiance circumstances (i.e., partial shade), COA employs the searching for the neighborhood's greatest worldwide operational voltage points while driving and chasing it.

5. USING DEEP TRANSFER LEARNING IN ORAL CANCER

5.1. Data Collection And Annotation

Assemble a large database of mouth cancer photos, with benign and malignant instances included. Make sure the dataset is varied, inclusive of numerous demographics, and reflective of the lesion characteristics. Each picture should be classified as benign or malignant to annotate the dataset, a task normally carried out by knowledgeable physicians.

5.2. Data Preprocessing

By deleting duplicate or poor-quality photographs, clean up the dataset. Create uniform picture dimensions by standardizing them. Utilize data augmentation methods, such as rotations, flips, and scaling, to broaden the training dataset's variety. Benign/malignant category labels should be converted to numerical format.

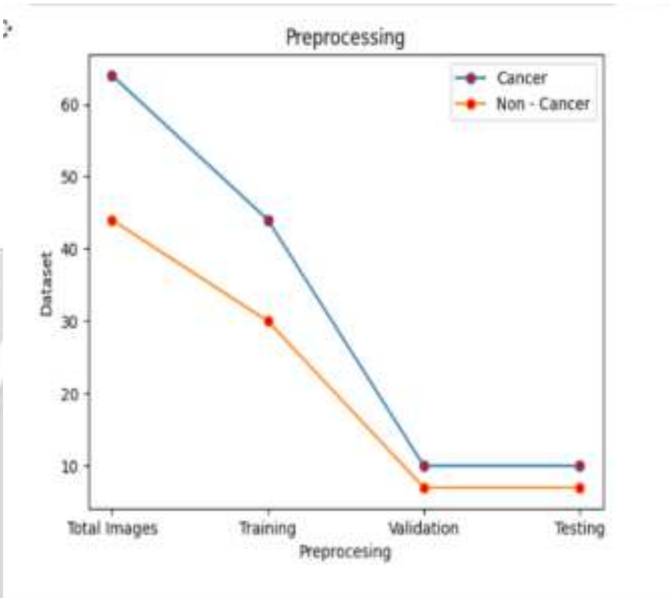

Fig-3: Pre-process dataset

5.3. Pre-Trained Model

A cutting-edge pre-trained deep learning model should be used as the foundation of your architecture. The options that are frequently used include DenseNet, ResNet, Inception, VGG, or EfficientNet. The pre-trained model need to have been developed using a sizable, multi-purpose picture dataset, such as ImageNet.

```
CANCER :
Total images:  64
Training:  44
Validation:  10
Testing:  10

NON-CANCER :
Total images:  44
Training:  30
Validation:  7
Testing:  7
```

Fig-4: Pre-Trained Output

5.4. Transfer Learning

Set the learnt weights and architectural parameters for the chosen pre-trained model. Add more layers to the architecture to add your own features for feature extraction and classification on top of the pre-trained model. Some of the early layers, known as the feature extraction layers, should be frozen to stop them from changing during training. By training the model on the oral cancer dataset, you may fine-tune it and update certain layers while still using the pre-trained model's information.

5.5. Accuracy

An important worldwide health issue, oral cancer frequently has poor patient outcomes due to late-stage detection. A potential approach to improve early cancer diagnosis is deep learning, particularly transfer learning. Accuracy is crucial in healthcare. It immediately affects the results and patient care. Accuracy is the capacity to correctly classify oral lesions as benign or malignant in the context of detecting mouth cancer. Correct identification guarantees that patients receive prompt care, increasing survival rates and lowering morbidity. The strength and variety of the training and assessment datasets serve as the foundation for efficient deep learning models for oral cancer early detection.

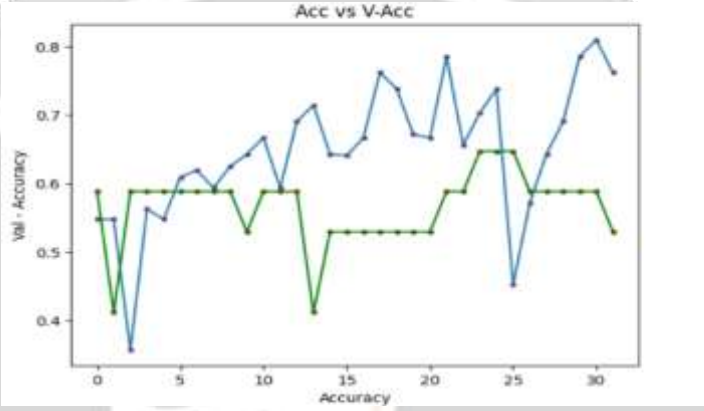

Fig-5: Accuracy graph

6. RESULT AND DISCUSSION

Using the benchmark dataset from the Kaggle repository, experimental confirmation of the suggested AIDTL-OCCM model was carried out. Photographs of the lips and tongue in two category: cancer (87 photographs) and non-cancer (44 pictures) are included in the collection. The suggested AIDTL-OCCM model produces five runs of confusion matrices. The graphic illustrates how effectively the AIDTL-OCCM model identified oral cancer in each run. During instance, the suggested AIDTL-OCCM model assigned 37 photos to the non-cancer category and 81 images to the cancer category during run-1. Similar to run-1, run-2 identified 28 photos as non-cancer and 84 images as cancer according to the suggested AIDTL-OCCM model. Similar to run-4, the suggested AIDTL-OCCM model identified 35 photos as non-cancer and 81 images as cancer in run-5.

Fig-6: Sample Images of Cancer Patients

```
from google.colab import files


def cancerPrediction(path):
    # Loading Image
    img = load_img(path, target_size=(256,256))
    # Normalizing Image
    norm_img = img_to_array(img)/255
    # Converting Image to Numpy Array
    input_arr_img = np.array([norm_img])
    # Getting Predictions
    pred = (model.predict(input_arr_img) > 0.5).astype(int)[0][0]
    # Printing Model Prediction
    if pred == 0:
        print("Cancer")
    else:
        print("Non-Cancer")

# Path for the image to get predictions
path = "/content/OralCancer/non-cancer/20190916_1428142.jpg"
cancerPrediction(path)

1/1 [==============================] - 0s 327ms/step
Non-Cancer
```

Fig-7: Prediction of Cancer/Non-Cancer According to the image

7. CONCLUSION

For the purpose of accurately identifying and classifying oral cancer, the authors of the current study created a specific AIDTL-OCCM model. A variety of operations are carried out by the AIDTL-OCCM technique as it is outlined, including DenseNet-169 feature extraction, AE-based classification, COA-based parameter optimization, and fuzzy-enabled pre-processing. In order to establish the ideal parameters for the AE model, COA is also used. Benchmark datasets were used as the basis for a wide range of experimental investigations, and the outcomes were examined from a number of angles. The suggested AIDTL-OCCM model performed better than other previous techniques, with a maximum accuracy of 90.08%, according to the findings of thorough experimental investigation. In order to classify oral cancer, the AIDTL-OCCM approach can be used as a useful tool. In the future, categorization of medical pictures for the detection of oral cancer can be done using sophisticated DL models.

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