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ORAL CANCER DETECTION USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract:

Introduction: Oral cancer is one of the foremost dangerous cancers which happens within the oral depth. Abuse of tobacco and smoking cigarettes are the essential chance variables for creating oral cancer [2]. Oral cancer conclusion at an early arrange can spare the lives of numerous individuals with appropriate treatment.[1]

Objective: The proposed work points at early location of possibly dangerous verbal injuries by the advancement of a mechanized illness determination framework. Building a large dataset of well-annotated oral injuries could be an essential key component [10]. A novel strategy to construct programmed oral cancerous picture classification computer program is given in this paper.

Methods: Within the display work, machine learning models and profound neural systems are utilized to construct a mechanized conclusion framework. By utilizing the starting information, which was assembled in this think about, Gullible Bayes, KNN, SVM, ANN, and CNN classification models are built for the computerized discovery and classification of verbal malignancies. An unused CNN arrange is outlined which comprises of 43 profound layers, whose arrange structure is motivated by the standard VGG-16 arrange [24].

Results: Execution investigation of distinctive machine learning models and profound learning models has been given. Result illustrate that the profound learning show has the potential to handle this challenging assignment of early location of verbal cancerous lesions.

Conclusion: It is watched from tests that distinctive classifiers can perform well in distinguishing verbal cancerous injuries. Especially, the profound learning CNN show appears tall exactness in separating typical and cancerous pictures

INTRODUCTION

According to the statistics of the World Health Organization, there are approximately 600,000 new casesof oral cancer each year and more than 300,000 deaths. The situation is true[8][9].
The burden of nasopharynx and pharyngeal cancer isespecially high in Central and South Asia.
Computer vision can be very helpful in diagnosing oral diseases compared to the naked eye. Diagnosis and classificatio n of oral cancer can be done by traditional machine learning and deep In the traditional machine learning process, dom ain experts need to identify the features used to reduce complexity and make them more visible to the learning algorith m.Insights into using traditional classification techniques such as support vector machine (SVM), Naive Bayesand near est neighbor (KNN) classifiers todivide oral diseases into lesions and abnormalities[7].

SVM is a supervised machine learning algorithm that can be used for classification. Naive Bayes is often used in classif ication problems and uses similar methods based on the probability of different features for different groups.
K_Neighbors is used to predict a list of unknown data by obtaining the most labeled K_nearest data, and the distance b etween cases is measured by a series of distance metrics. Deep learning is a subfield of machine learning that works on artificial neural networks that are inspired by algorithms brain structure and function. ANN (Artificial A neural network) can be trained on many images of both benign and malignant lesions. By learning nonlinear v, the model can tell itself whether the image is malignant or benign. So, no domain is needed in deep learning expertise for feature extraction. In

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the presented work, class is the ossification of oral images into benign or malignant images performed using a deep learning model using CNN (Convolutional Neuron Networks), which is a type of ANN [19].

CNNs consist of several layers of artificial neurons. The behavior of each neuron is defined by its weights. Each CNN consists of 4 layers: input layer, convolution layer, aggregation layer and fully connected (FC) layer. Con the convolutional layer extracts feature maps from the input image using filters and a pooling layer replaces the output network at certain locations by deriving summary statistics from the near east. This leads to a reduction in spatial size and thereby reduces the computational effort. Neurons in full scale connected layers have full connectivity with all neurons within previous and next layers. The FC layer helps with this map representation between input and output. On classify output, generally SoftMax layer is used in image classification. CNNs are trained using labeled datasets listed with the appropriate classes. CNN is learning the relationship ship between class labels. For the input image shown in Figure 1, feature maps extracted by convolutional layer are shown in Figure 2

LITERATURE REVIEW

Different researchers tried different machines and depths learn image classification techniques normal and abnormal images [4]. Licheng Jiaoet al a survey of next-generation deep learning techniques that can be used for image processing tasks [5]. Three series deep learning models namely CNN series, GAN series and ELM series serial networks and their role in image processing tasks were described. These are widely used in painting processing today when these techniques are different depth and types of networks that enable image processing tasks now easier. Daisuke Komura et al. 9 used ma Chinese learning techniques such as SVM, random forest, CNN, k-means, autoencoder and principal component analysis for histopathological analysis of the image.

Before applying the machine learning methods, feature extraction and classification cancer and cancer-free patch refills are performed.

Anne Humeauet al. Seven classes of texture properties, e.g traction methods, their advantages, disadvantages and possibly applications are reviewed. Large amount of texture datasets which the authors use to test and compare functionality extraction algorithms were described. For very high resolution of remote sensing images, the authors suggested histogram-based attribute profiles that enable modeling texture information from attribute profiles [26]. Discussion on the subject of controlled, uncontrolled and semi-super see feature selection techniques that reduce computation time, increase accuracy and assist in removing redundant and irrelevant data were presented by Jie Caiet al. Their use in many areas such as image loading, text mining, error diagnosis sis and other areas were reviewed by the authors. Skin segmentation using Yellow-Chrominance blue-Chromi nance red (YCbCr) and red-green-blue (RGB) mod ells reported by Shrutiet al. The authors developed computationally efficient and accurate skin approach cancer detection that can be used in real time. The results show that the YCbCr model is better than the RGB model in the segmentation and classification of skin lesions. The authors developed a deep learning model classification of malignant lesions of the oral cavity using CNN technique [3].

DATA COLLECTION

A total of 630 oral images have been used so far work for oral image classification. These pictures were few and far between downloaded from the internet and several others were collected from various hospitals by consulting oral specialists[6]. FROM 1200 lesion areas were cropped on these images and as a consequently, we obtained separate images of lesion areas. Out of these 1200 lesion images, 600 are malignant images and 600 are normal images. Figure 3 and Figure 4 are different end spots of several normal and malignant images from data file. Benign patches are marked as B001, B002 and so on. Malignant spots are marked as M001, M002, and so on. A feature vector was created by extracting the useful features from these images of lesions and then newly ob. The preserved dataset is used in machine learning models for testing purposes.

For the deep learning model, the images are lesions expanded by 9600 images. Then there are these pictures used to train the network

MATERIALS AND METHODS

The details of the proposed work for the detection of malignant tumors of the oral cavity are clarified in Figure 5. The input to the disease diagnosis system is an oral RGB image, this input the image is then subjected to a segmentation process to select the lesion area [15]. After segmentation, features are extracted from the lesion area; these features are used to classify the image using SVM, KNN, Naive Bayes and ANN models. A CNN takes an image of a segmented lesion as input to the network and classifies the image as normal or malignant. The details of this process are detailed in the following sections [25].

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In this process, the lesion area is extracted from the input image. First, the input RGB image is converted to YCbCr color space and subsequently a mask of the lesion area is created into blue differential saturation (Cb) and red differential saturation intensity values (Cr). Oral cancer is of two types of spots of lesions - white and red spots of lesions. If the mean Cr value of an input image is lower than a predefined threshold, this image will contain white spots; if the area contains a mean Cb value higher than the average, a white spot lesion mask is created using the Cb intensity. The Cb value of the whole image, then this area is considered to be white spot on the lesion. If the mean value of Cr of the input image is greater than a predefined threshold value, then enter the image will have red spots, a mask of lesions with a red spot is created using the Cr intensity if the region contains moderate Cr a value greater than the average Cr value of the entire frame this area is considered a red patch of lesions. After creating the lesion mask, contours based on the active area segmentation is performed to select lesion areas in the input image based on the mask and the lesion which has a wider area is considered the final exit lesion and then this lesion is extracted as a separate image. Figure 6 shows segmentation details of oral lesions [22].

Figure 1: Input image for CNN

A feature vector with 44 elements is created by grayscale extraction level co-occurrence matrix (GLCM), gray-level run length matrices (GRLLM), fractal elements, Gabor elements and Color features from lesion images. Extracted properties are Energy, Homogeneity, Contrast, Correlation, Short Term emphasis, long-term emphasis, gray-level nonuniformity, Run length unevenness, run percentage, low gray level emphasis on run, high emphasis on gray level, low on short run Gray Level Enhancement, Short-term Gray Level Enhancement, Long-term low grayscale, long-term high grayscale, fractal dimension, fractal lacunarity, standard deviation, Gabor mean square energy, Gabor mean amplitude, mean and standard deviation of RGB, Hue-Saturation-Value (HSV) and YCbCr color components [16][23].

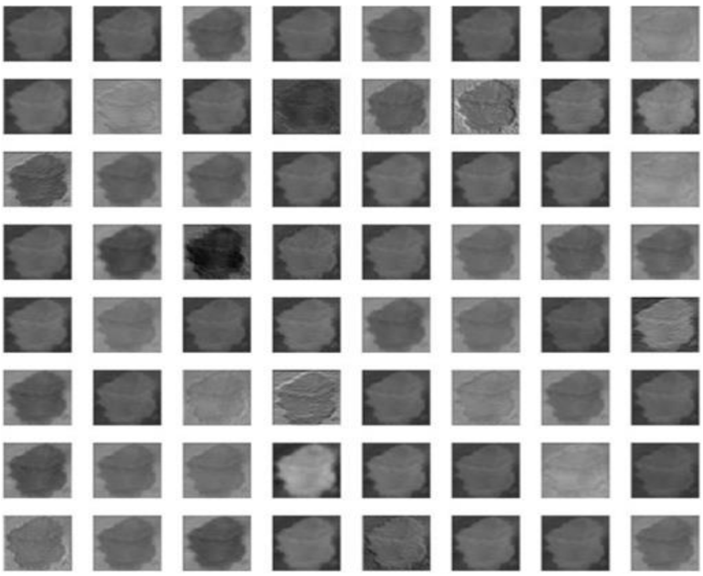

Figure 2: Feature Maps extracted by a convolutional layer

Irrelevant and redundant elements from the extracted elements were removed and only the most relevant elements are selected using statistical feature selection methods[21]: Minimum Redundancy Maximum Relevance (MRMR) and box plot methods. By virtue of the rank so assigned element selection method, the best 19 elements are selected. Selected features are listed in Table 1.

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Table 1

Methods	Features
GLCM	Homogeneity
GLRLM	Long Run Emphasis
	Gray-Level Non-uniformity (GLN)
	Run Percentage (RP)
	Low Gray-Level Run Emphasis (LGRE)
	Long Run High Gray-Level Emphasis (LRHGE)
Fractal Features	Fractal Dimension
	Fractal Lacunarity
Gabor Features	Gabor Mean Amplitude
	Gabor Square Energy
Color Features	Mean of Red value
	Mean of Blue value
	Mean of the hue value
	Mean of the Saturation value
	Mean of HSV values
	The standard deviation of RGB values
	The standard deviation of the Green value
	The standard deviation of Hue vale
	The standard deviation of the Saturation value
	The standard deviation of blue difference chroma value
	The standard deviation of red difference

Figure 3: Normal Oral Images.

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Figure 4: Malignant Oral Images.

SVM is a supervised machine learning algorithm that can be used for the classification process. Mean Gaussian An SVM model that uses meth is used for classification z called the kernel trick to modify the data and then to the base on these changes identifies the optimal boundary between possible output.

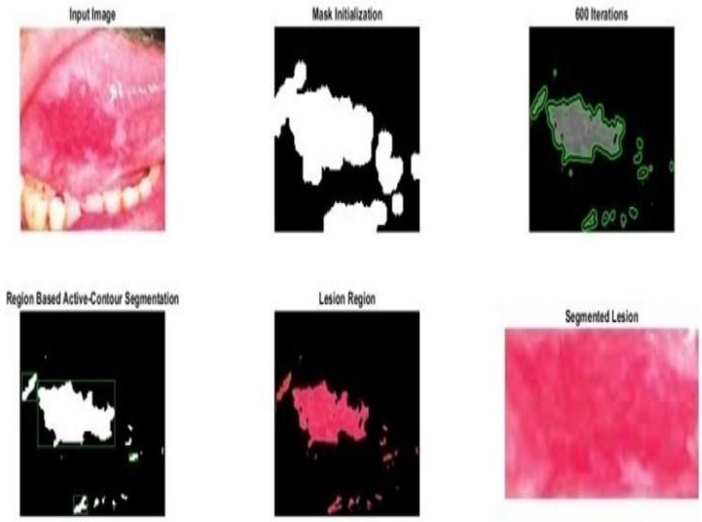

Figure 5: Oral lesion segmentation.

A modified version of KNN, i.e. weighted KNN, is used classify the image based on selected features from the lesion region. The performance of this method is completely de depending on the training set and hyperparameter choice K. For the current work, a value of 10 is chosen for K. The Naive Bayes classifier is a simple probabilistic classifier which is based on Bayes theorem. For current classification cation, a Bayesian classifier with varying kernel density is they took advantage of it. A Feed-Forward Artificial Neural Network is used to classify images based on selected features from the lesion image. A dataset of 19 features extracted from lesion images is used to train the network. The network consists of 20 hidden layers and 1 output layer. The ANN network architecture is shown in Figure 7.

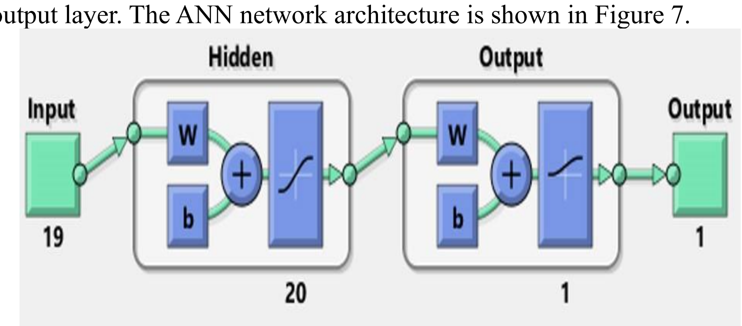

Figure 6: Proposed ANN Architecture.

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A new convolutional neural network is created for oral dis easy detection which has 43 layers. Architecture A CNN is shown in Figure 8. This network includes 10 convolution layers, dose normalization layer is used to normalize the output of the convolution layer, and the ReLU layer activation function is used. The max-pool layer is used for association. 3 fully coupled layers are used with 1024, 512, and 2 nodes in the respective layers. The output is predicted using SoftMax layer. This CNN takes 64x64 RBG images as input and classifies them as benign or malignant images.

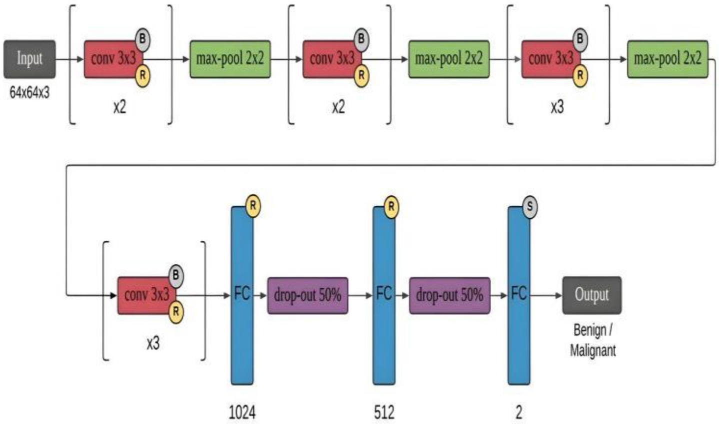

Figure 7: Proposed CNN Architecture.

Dataset	Number of images used
Training and validation	8000
Testing	1000
Validation	600

Table 2

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Dataset	Number of images used
Training and validation	1000
Testing	200

Table 3

The training accuracies of the classification models are given in Table 4. Classification test performance measurement cation models are listed in Table 5.

Models	Accuracy
Naive Bayes	90.01%
KNN	94.4%
SVM	98.3%
NNY	99.4%
CNN	99.3%

Table 4

Evaluation measure	Naive Bayes	KNN	SVM	ANN	CNN
Precision	87.18%	87.50%	96.34%	98.18%	97.00%
Recall	82.93%	93.90%	96.34%	98.54%	97.67%
Fi score	85.00%	90.59%	96.34%	98.18%	97.51%
Specificity	91.53%	90.68%	97.46%	95.55%	97.34%
Accuracy	88.00%	92.00%	97.00%	97.00%	97.51%

Table 5

A modified version of KNN, i.e. weighted KNN, is used classify the image based on selected features from the lesion region. The performance of this method is completely de depending on the training set and hyperparameter choice K. For the current work, a value of 10 is chosen for K.

The Naive Bayes classifier is a simple probabilistic classifier which is based on Bayes theorem. For current classification cation, a Bayesian classifier with varying kernel density is they took advantage of it.

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RESULTS

Dataset

A dataset consisting of 19 feature values of 1200 lesions images are used for training using SVM, KNN, Naive Bayes and ANN models. Details on training and testing datasets for the models used are shown in Table 2. Images of segmented lesions are used for training and testing the CNN model and their details of the dataset are shown in Table

3 [13][27].

Dataset	Number of images used
Training and validation	1000
Testing	200

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Table 5

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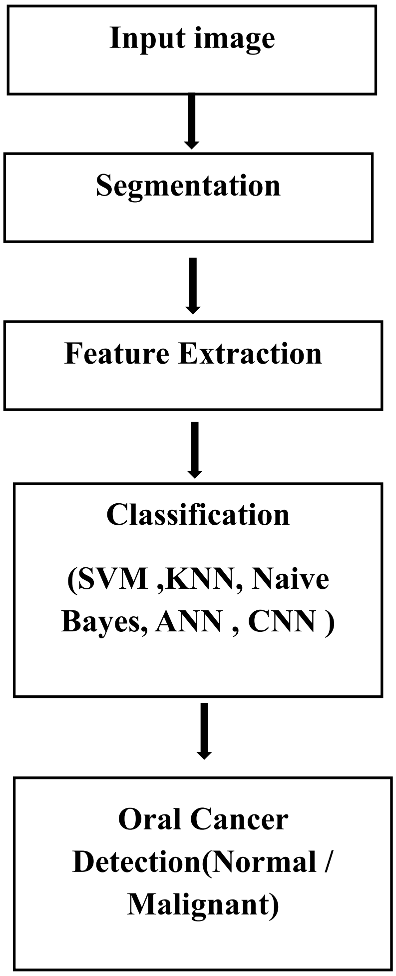

Figure 7: Proposed oral image segmentation and classification model.

DISCUSSION

From the obtained results, among the machine learning classification models, i.e. Naive Bayes, KNN and SVM, SVM ranks the model performs well compared to the other two models [12][14]. CNN model performs better compared to ANN. Although the performance of ANN is almost the same as CNN, CNN it still stands out as the best because of its ability to learn better functioning itself when looking at overall performance each CNN classification model outperforms all other models with 99.3% training accuracy and 97.51% testing accuracy. Also, ANN and SVM models work almost the same in terms of CNN performance [17].

CONCLUSION

There are several machine learning and deep learning in this article were classification models for oral cancer detection discussed. Results of classification models for cars mating early detection of oral cancer was a demon layered. The desktop software is built using MATLAB for classification whether the image is malignant or normal using any of them models that are listed in the post and report them generated accordingly. The promising results of the model show the effectiveness of deep learning and suggest that it has potential to solve these challenging tasks.

FUTURE SCOPE

It will be possible to collect more images in future work enrich the dataset and improve accuracy models using various fine-tuning techniques and aug mentation. The main goal will be the implementation of semantics segmentation to select the lesion area from the input image to improvise model accuracy results[11][18].

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