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Skin Cancer Detection Using VGG-16

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Abstract: ***Skin cancer is a dangerous disease. Benign and malignant melanomas are one of the skin cancer diseases. Melanoma is a highly dangerous disease. It can be curable if it is detected early. Benign can be cured easily but malignant cannot be cured fastly. Benign and malignant melanoma appears in the early stages while differentiating them. Different methods have been used for differentiating them. Skin cancer can be detected in early stages by visualizing with clinical screening by dermoscopic analysis. Detecting automatically skin lesion is a typical task. Skin cancer symptoms are small blood vessels visible, thickened patch, ulcers and bleed. Skin cancer detected by capturing images with a skin magnifier with polarized light and diagnosed with deep learning classifier in which data augmentation and weights can be added to it. In this CNN classifier is used in which RESNET-50 and VGG-16 were used in which image were resized and weights were added and then the augmentation of the data can be done.***
Keywords: Vgg-16, ResNet-50, Malignant, Benign, Malignant, Convolutional Neural Network.

I. INTRODUCTION:

Skin cancer occurs at a place where skin exposed to sunlight and some parts which are not appeared to sunlight. It has abnormal growth of skin cells. Early detection can save a human life up to 95%. Many researchers are researching about this disease. So many cases were recorded in the past. Detection of this disease at the peak stage may lead the patient to die. Many of the patients may die because of not detecting early. Previously, practitioners used to examine the lesion area and then decide whether cancer is found or not. Sometimes, some of the assumptions on patient may be wrong then the patients may die sometimes. From 2016 several datasets were introduced so that it can easily detect by using the datasets. If the patients have the same conditions then he or she might have cancer and then they should go for biopsy and get the results whether cancer is there or not. Datasets are very much useful for skin cancer detection. Now-a-days skin cancer is a widely growing disease. To eradicate this many pathologists were researching about this disease. About millions of cases were recorded in a single year. If the lesion is determined in the early stages the patient survival rate is up to 95%.So that they can save a human life. Human life is a very precious thing in our life. So that different practitioners are searching for the better results. Different techniques were used for getting better accuracy results. A practitioner selects the technique which gives the better results.

If it is detected at the peak stage then the patient may die. Many of the patients died because of not detecting early. Previously, practitioners used to examine the lesion area and then decide whether cancer is found or not. Sometimes, some of the assumptions on cancer patient may be wrong then the patients may die sometimes. Then dermoscopy of image analysis were done in which the suspected area will be biopsied in which smaller amount of skin is cut and tested to find whether cancer is present or not. From 2016 several datasets were introduced so that it can easily detect by using the datasets. If the patients have the same

conditions then he might have cancer and then they should go for biopsy and get the results whether cancer is there or not. Datasets are very much useful for skin cancer detection.

The images which are acquired with the help of skin magnifier with polarized light then deep learning classifier can be applied for it to classify images based on the disease. In this deep learning classifier is used for classifying benign or malignant so that benign case is a simple case so that survival is more. If the condition is malignant then it should be recognized early and should be treated as soon as possible. By deep learning classifier some of the malignant cases can be recognized as benign so that the patient lifespan decreases.

Review of Literature Survey:

J. Malvehy [2] proposed Helsinki guidelines are good clinical practice. Participants were screened according to inclusion and exclusion criteria. Dermoscopic photo taken and their medical history considered and this comes under clinical evaluation. Histopathology evaluation team (3 members) considers these agreements and if any dermoscopic image disagreement then it may be informed within 7 to 10 days or when the patient arrives.

Haenssle HA [3] proposed that in this 300 images with high quality were considered in which 20% melanomas and 80% benign. No overlap between datasets for training or validation and testing was allowed. Two dermatologists select 100 images from 300 images for diagnosis increasability. Set-100 used for CNN testing in comparison to dermatologist. In level-1(<2 year experience) reader study asked for diagnosis of melanoma or benign nevus. Then after 4 weeks they indicated their diagnosis and management in level-2(2-5 years experience) which include additional clinical information for dermoscopy images and closes for 100 images.

Codella [5] proposed that it combines deep learning, support vector machine and sparse coding learning algorithms. It used unsupervised learning to eliminate annotated data of target task to learn good features. Early diagnosis can be useful for the survival of patient as 95% with the help of dermoscopy.

Andre G.C [10] Dermatologists examine the lesion and age. Dermatologists use the Dermoscopy technique in which it can't be viewed by our naked eye. Skin cancer should be detected by Computer-Aided-System. In this dataset of images which were captured by Smartphone and clinical data of patient were considered then the aggregation of images and clinical data done then calculate the performance with and without the mechanism. By applying aggregation method it gives balanced 7% accuracy which results automated skin cancer detection.

Koelink CJL [11] proposed in this skin cancer is examined by General Practitioners (GP). Results of that lesions should be examined by the GP and the results mostly or benign. In primary care it is a challenge for GP to detect Skin cancer in early stages. Cost-effective algorithms and tools are needed with a high diagnostic accuracy (DA). In the secondary dermoscope increase diagnostic accuracy so that experienced examiners may add some useful information when is in the case of non-melanocytic condition to improve the accuracy and to be cost-effective.

Annessi G [14] proposed For accurate diagnosis of lesions three algorithmic methods (qualitative pattern analysis, the ABCD rule of dermoscopy and the ELM 7-point checklist) are useful for distinguishing the benign and malignant melanocytic. It compares the results of 198 difficult melanocytic lesions i.e

sensitivity, specificity, diagnostic accuracy and to determine the significance of distinct ELM structures in the diagnosis of atypical melanocytic nevi (AMN) and thin melanomas (TM).

II. PROPOSED WORK:

The dataset is taken from the Kaggle which is malignant vs. benign. It consists of 1497 pictures of malignant moles and 1800 pictures of benign classified moles. The lesion pictures are resized to (224x224x3) RGB. In this model it classifies whether a mole is benign or malignant. The pictures have resized to 224x224 and load the pictures into numpy array using their RGB values. Pictures should be labeled and the data added to training set and shuffled.

In this approach VGG-16 and RESNET-50 were used in which accuracy increases Skin cancer is the most dangerous disease if it is not detected early and the chance of the death of the patient is high. Patient might be cured from it early if detected early and there is no chance of death. ResNet used to solve the gradient diminishing to skip the connection and move to next layer and continue to train the images. CNN models can vary the data deeply by Resnet models.

Images were transferred into array IMG all the data are transferred into training and testing data in the form of array. Then the training images of benign and malignant are concatenated and the testing images were concatenated. The data is arranged and shuffled randomly. Next displays the first 15 images which are of malignant and benign. The data generator generates the data. Model is defined with Resnet50 and the top is declared as false and tensor is defined as none and the shape of the image is 224x224x3 and classes are whether it is malignant or benign. Model function is flattened and the batch normalization has applied and the activation is relu and sigmoid is applied and the model is compiled with the loss of binary cross entropy. The model has trained with batch size of 64 and the epochs 150 are considered. The validation accuracy obtained for training data is 0.8900. For the testing model the accuracy score obtained between y_test and list is 0.87878787.

METHODOLOGY:

Models were applied i.e., with vgg-16, 80% accuracy with 100 epochs firstly images were resized to 224x224x3 then weights were added to it and resnet-50, 87% accuracy with 100 epochs images were resized to 224x224x3 and weights were added to it.

```
#Define model with different applications
model = Sequential()
#vgg-16 , 80% accuracy with 100 epochs
#model.add(VGG16(input_shape=(224,224,3),pooling='avg',classes=1000,weights=vgg16_weights_path))
#resnet-50 , 87% accuracy with 100 epochs
model.add(ResNet50(include_top=False,input_tensor=None,input_shape=(224,224,3),pooling='avg',classes=
2,weights=resnet_weights_path))
model.add(Flatten())
```

```
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(Dense(1, activation='sigmoid'))
model.layers[0].trainable = False
model.summary()
```

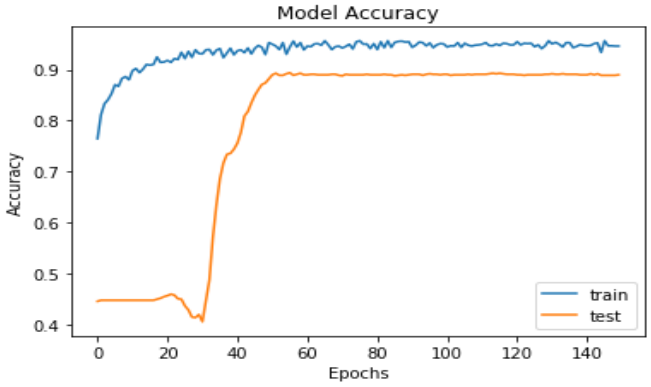
Then train the model:

```
# Train model
batch_size=64
epochs=150
History = model.fit_generator(datagen.flow(x_train,y_train,batch_size=batch_size),validation_data=(x_val,y_val),
                              epochs= epochs, steps_per_epoch=x_train.shape[0]//batch_size,verbose=1,callbacks=[red_lr])
```

The graph is plotted between model_accuracy and accuracy, epochs for train and test images. Then the prop_class and mis_class arrays were created and the data is taken from Y_test. If Y_test and list items are equal it is appended to prop_class. If the Y_test data is not found in list then they are appended to mis_class array. The images were classified and displayed properly or not can be known by using the predicted result and actual result.

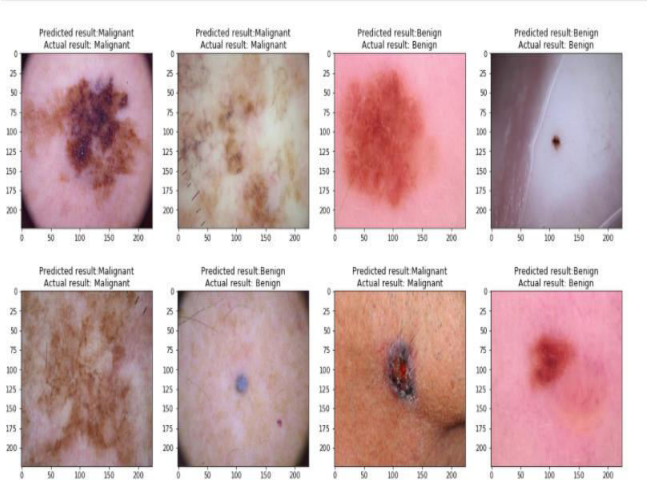
III. RESULTS AND DISCUSSION:

In this graph is plotted between accuracy and epochs for training and testing images. The accuracy we got is better results. Training data can be shown in the form of blue line and testing in the form of orange line. In the graph epochs are 140 and accuracy for testing images is 0.8666 and then constant.



Graph 1: Accuracy of the testing images over training images.

The predicted results of the trained model are shown in the below figure:



Different methods were considered and the accuracies were calculated for it. Performance analysis of different classifiers like ABCD rule, GLCM feature and shape feature were applied to the model accuracies, sensitivity and specificity were calculated using SVM, Random Forest and KNN algorithms were available in Table 1, Table 2, Table 3.

Table 1: Performance analysis of various classifiers for ABCD rule:

Parameters	**Classifiers**		
	SVM	Random Forest	KNN
Accuracy (%)	85.62	76.87	69.54
Sensitivity (%)	86.2	78.43	71.32
Specificity (%)	85.91	75.31	67.76

Table 2: Performance analysis of various classifiers for GLCM feature

Parameters	**Classifiers**		
	SVM	Random forest	KNN
Accuracy (%)	85.72	74.32	65.39
Senstivity (%)	86.51	76.85	68.27
Specificity (%)	83.76	71.79	62.51

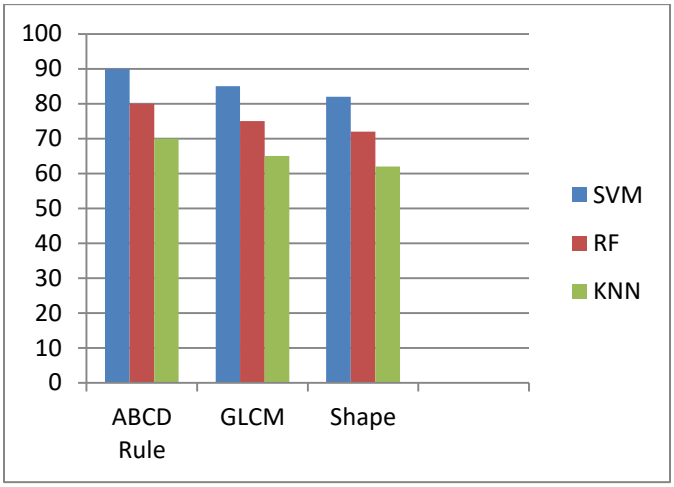
Table 3: Performance analysis of various classifiers for shape feature

Parameters	**Classifiers**		
	SVM	Random forest	KNN
Accuracy (%)	82.31	71.97	62.19
Sensitivity (%)	85.32	74.75	65.72
Specificity (%)	78.86	69.19	58.66

By using CNN architecture like VGG-16 and RESNET-50 accuracy is 86.6.

Graph:

A graph is drawn between the ABCD rule, GLCM feature and shape for SVM, Random forest and KNN classifier. It is represented in graph 1. The graph is marked between the SVM, Random forest and KNN algorithm.



Graph 2: Analysis of accuracies for various classifiers.

It is reported that the skin cancer can be detected by using the elementary dermoscopic device which diagnosis malignancy utilizing Deep Learning and sonifictaion algorithm. The data is gathered from clinical studies and arranged as a form of dataset and different algorithms were applied for the dataset so that it can calculate the accuracies based on the highest accuracy the algorithm is considered and used for the recognition of the disease early.

ABCD rule detects melanoma mostly by acquiring the few changes when compared to the other skin cancerous diseases. General Practitioner is concerned about your skin, if any changes occur then they recommend to the dermatologists who are expert in diagnosing the skin cancer. Asymmetry - shape of two halves may differ in size. Border – some parts of the skin are blurred and irregular. Color - Black, pink and brown color shades are available on the skin. Diameter - If any changes in the size of melanoma then report it to your doctor. Mostly it is of size 6mm. In ABCD rule SVM will give better accuracy while compared to the Random Forest (RF) algorithm and KNN. In GLCM and shape, Random Forest (RF) algorithm and KNN has less accuracy than the SVM.

IV. CONCLUSION:

As skin cancer is a growing disease now-a-days, and there is a huge loss of lives of so many people. If it is detected early there is no problem. If it is detected in peak stages then the chance of survival rate drops from 99% to 14%. Different methods were used for detection of cancer early but some give good results but some don't give what we have expected accuracy of detection should increase so that cancerous skin can be detected early and proper treatment can be given to the patient. Deep Learning has many models to overcome the less accuracy methods.

First dataset is gathered then the images were assigned to train images and test images then the train and test images were merged then different deep learning mechanisms were used i.e., RESNET-50 and different mechanisms were applied to the dataset. Then the compiled data will give the results and then we can find

which is depicted as malignant or melanoma if the accuracy of the data increases then it will be used for detection of skin cancer. In our algorithm accuracy increased and it can detect the data properly i.e., whether it is malignant or benign.

V. REFERENCES:

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