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COMPARATIVE ANALYSIS OF SKIN CANCER IMAGE CLASSIFICA-TION USING KERNEL-VARIANT SUPPORT VECTOR MACHINES AND CONVOLUTIONAL NEURAL NETWORK-BASED DEEP LEARN-ING APPROACHES

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Abstract

Early detection of skin cancer significantly reduces the risk of developing malignant tumors such as melanoma. Skin tumors can be either benign or malignant, and their classification relies on visible symptoms and characteristic features. This study utiliz-es a clinically validated image dataset containing over 25,000 skin tumor images for classification purposes. From these images, categorical and continuous features were extracted, resulting in a structured dataset of 10,000 images described by eleven at-tributes related to cellular properties. Initially, a Support Vector Machine (SVM) clas-sifier was trained and evaluated on this dataset. The SVM models employed four different kernel functions—Linear, Polynomial, Sigmoid, and Radial Basis Function (RBF)—to map the features into higher-dimensional spaces. Their classification per-formance was assessed using metrics such as accuracy, specificity, and sensitivity. In the second phase of this research, the same dataset was used to develop and evalu-ate deep learning models based on Convolutional Neural Networks (CNNs). Three custom CNN architectures were designed by adding additional convolutional, pool-ing, and hidden layers, and optimizing various parameters for improved feature ex-traction and classification performance. Additionally, pre-trained models such as VGG16 and ResNet50 were employed for comparative analysis. The performance of these CNN-based models was measured and compared against the SVM classifiers to determine the most effective approach for skin cancer image classification.

Keywords: Support Vector Machine, CNN Classifier, VGG16, Diverse Kernels, ResNet50.

I. INTRODUCTION

One of the prime cause of Melanoma is UVR(Ultra violate rays) as per the reports by WHO(World Health Organization)[1]. As per the study carried out, in Europe the

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Melanoma patients are ranging from 5 to 14 per million[2].

Early detection of melanoma can help to cure the melanoma. Two factors mainly responsible for the melanoma aregeographical region and skin texture. Skin texture can help to predict the possibility of melanoma. Skin texture depends upon the skin pigmentation and sunlight condition in that specific geographical region. Pigmenta-tion of the skin is due to the Melanin available in the cell of skin. When the skin is over exposed to the Ultra violate rays of sunlight, it generate deformation in the Mel-anocytes cells. Melanocytes cells are responsible of producing Melanin. Deformation in melanocytes cells causes the Melanoma. Similarly, less exposure to the sunlight also causes the deformation in Melanocytes. It is observed that melanoma is ob-served very high among the people of age less than40 in European countries where the sunlight exposure is less[4]. It is possible to cure the melanoma if detected at early stages although it is considered as fatal if not treated at early stage. Melanoma is high risk category of skin cancer type. It is more usual category of malignant lesion com-pared to other categories of skin lesions types [14], [15]. It is fastest approaching and growing category of skin cancers which caused higher numbers of patients suffering and increasing in numbers every year[16], [17].

Visible symptom is generation of mole with non-uniform shape and having a thick border of size above quarter of inches separating the mole and the skin. But in certain cases it is also observed that the melanoma is not necessarily having mole[4]. Neo-plasm is the cause of uncontrolled growth of cells that results in tumor or cyst. As per one study by the WHO(World Health Organization), over 1.81 million estimated cas-es of neoplasm are expected by the beginning of the year 2021[5]. This condition of neoplasm is of two types: benign or malignant. The benign types are not fatal one and are curable; whereas the malignant become fatal if not cured at appropriate time.

Condition of neoplasm is evident and visible. However, it is essential to identify and distinguish among the benign and the malignant. By classifying the image as benign or malignant at early stage can help to save the life of patient. There are three important characteristics that distinguish benign and malignant conditions: (i) Shade (ii) size and (iii) Border shade.

The shade of suspected region is having darker shade in case of the malignant compared to the benign. Size of the malignant condition is normally higher than the quarter of inch compared to the benign which is usually less than the 0.25 inch of size. In case of benign type the outer border of the condition is having lighter shade compared to the darker one in case of malignant.

Early detection of melanoma condition is possible usingseveral approaches. Among all these approaches two of them are more popular: (i) Feature extraction of the images in terms of continuous and categorical data and then classify it based on the obtained dataset of features. (ii) Image processing by using

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image segmentation, identification of region of interest and extracting the feature in process to train the neural network and classify based on the trained network. Ultimately whether its classifier built using feature sets based dataset or classifier based on image dataset using convolution neural network; the goal is to build a classifier that classify the skin cancer condition as benign or malignant.Various approaches are proposed and cur-rently in use to classify skin lesion based on clustering, classifying and neural based algorithms.

1.1 Image Database

Several approaches applied are based on machine learning algorithms for relevant work to classify the lesion as benign or malignant need to be compared with the im-age processing using deep learning. Neural network in unsupervised mode is capable to evaluate large number of features compared to the limited features used to train the machine learning based classifiers. The performance evaluation can give fairly good idea about the relevance of the classifiers and possible enhancement. The cur-rent study is comparing Support vector Based classifiers. Dataset used for the study is open source dataset containing skin lesion images which are clinically verified benign or malignant provided by ISIC(International Skin Imaging Collaboration) available through kaggle open database of year 2019[6]containing 25,331 images[7]. The da-taset is consists of clinically verified 13,330 malignant images and 12,001 benign images.

II. RELATED WORK

Several works in field of early detection of skin cancer and classification among the benign or malignant applying different algorithms are carried out so far. As per the study carried out by Tajeddin NZ, Asl BM proposed model based on contour prop-agation using two component speed function to identify the peripheral characteristics of the lesion. Using Drugman's transformation the model proposed mapping of log-polar space[8]. The study claimed to use only four features and obtained average of 97% sensitivity and 100% specificity using PH2 dataset on comparison of melanoma and nevus recognition. As per the study carried out by Tabatabaie K et al.[9], based on Independent Component Analysis(ICA). It extracts features and textures of skin lesion using clinically verified skin cancer images. Using the obtained characteristics along with the color features of the lesion are used to build classifier based on Sup-port Vector machine to classify melanoma and benign images. The study depicts classifier that classify with 88.7% accuracy[9].

Extraction of feature approach proposed by Serban ED et al., is based on Reflec-tance confocal microscopy. It is an optical imaging technique in which the image is obtained using laser diodes' monochromatic light that penetrates through the cell that generate image on detector by passing through a filter. This methodology is different than the conventional microscopy technique. It allows horizontal view of the skin at resolution of cellat lateral dimension range

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from 0.5 to 1.0 µm and 4.0 to 5.0 µm in axial dimension[10].As per the study carried out by Efimenko M., et al., in which they review various recent findings related to neural network based classifiers. The study reveals that neural network based classifiers provide higher specificity, accuracy and sensitivity compared to the findings by the dermatologists. The study outcomes shows that the features extracted by the neural network based classifiers are more reliable and accurate that yield higher accuracy to classify compared to the human eyes specifically in cases of early detection of melanoma[11].Classifier proposed based on ensemble of Convolution Neural Network by Harangi B. depicts that classi-fier based on machine learning have drawback of extracting features from the thou-sands of labeled images for purpose of training and testing. The approached carried out by the study classify the dermoscopy images in three classes: seborrheic kerato-sis, nevus and melanoma. The proposed classifier is based on aggregation of different fusion-based methods that select most appropriate performing CNN model and use its weights[12]. Another study carried out by Tanaka M, et al., proposed ResNet-18 based classifier which is reinforced by metric learning. It is used to avoid the problems of overfitting for training data those results in increasing the reliability. The study carried out using large dataset having more than 70 thousand images of more than 13 thou-sand patients. The classifier performs significantly well providing accuracies range from 0.579, 0.793 and 0.863 for Top-1, Top-3and Top-5[13]. Pham, T.-C., et al. states in their findings that Convolution Neural Network is highly reliable and in wide use due to lack of labeled data to apply machine learning based classifiers. The study used data augmentation to overcome the problem of limited dataset. Performance matrix of the study depicts Area under Curve (AUC) as 89.2% versus 87.4%. The findings of the study show that the augmentation of medical images can result in higher accuracy and classifier performance [18].

2.1 Objective

Two approaches are aimed to analyze classification of skin lesion images. First approach is to use the extracted features of the image dataset consists of continuous and categorical types eleven attributes.

(i) To build classifier using SVM(Support vector machine) algorithm and applying four diverse kernels to analyze performance of the model.
(ii) To build classifiers using Convolution neural network using the lesion images. To build three different customized classifiers based on CNN by modifying convo-lution layers, pooling layers and filters.
(iii) To build two classifier models based on efficient classifiers ResNet50 and RGG16 using same image datasetand analyze their performance.
(iv) To compare, evaluate and analyze performance matrix of classifier models based on SVM using diverse kernels, CNN based three customized classifier

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models and ResNET50 and RGG16 based classifiers by obtaining their performance matrix.

(v) Performance evaluation and comparison of modelsare based on accuracy, specificity, sensitivity, recall and precision.

III. METHODS AND METHODOLOGY

Image dataset obtained from the open data source available through the kaggle® provided by ISIC(International Skin Imaging Collaboration) which contain clinically verified 13,330 malignant images and 12,001 benign images. These images are hav-ing uniform size of 250 x 250 pixels and three channels. The image features are ex-tracted usingcustomized Neighboring Differential Analyzer (NDA) algorithm.

Using the NDA algorithm, dataset consists of eleven feature sets are extracted based on differential values of existing pixel and the neighboring seed pixels' mean feature values. These eleven features distinguish malignant and benign images based on Mean_of_Read, Mean_of_Green, Mean_of_Blue, orientation, perimeter_distance, median_of_Read, median_of_Green, median_of_Blue, intensity, posi-tional_axis(edge, border, center). Finally the Category(Benign, Malignant) feature will act as target attribute of the features set.

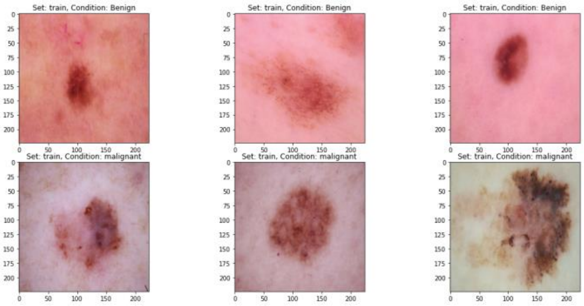

Fig.1.Benign and Malignant images obtained from the dataset

3.1 Analyzing dataset using Support Vector Machine(SVM)

The dataset is divided in training and testing set in ration of 80%-20% using four foldsbased on random selection mutual exclusion method. Each fold is trained using classifier based on Support Vector Machine (SVM) and tested. Four different kernels are used to analyze the performance of each of the four folds. The averages of all four folds are obtained to analyze their final performance matrix.

Linear Kernel based: Linear kernel is linearly separable handling large numbers of features. It is more efficient in case of text classification datasets.

$$k(X, Y) = 1+xy+xy\,\min(x, y) - ((x+y)/2)\,\min(x,y)2 + 1/3(\min(x,y)3) \qquad (1)$$

Polynomial Kernel: Polynomial Kernel is widely used in case of Image processing problems. Parameter d signifies the degree of polynomial.

$$k(X_i, X_j) = (X_i \cdot X_j + 1)d \qquad (2)$$

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Radial Basis Function(RBF): RBF includes Laplace Radial Bias function and Gauss-ian Radial Function. It is normally used in cases where data knowledge is unknown.

k(Xi , Xj) = exp (- γ | | Xi – Xj | | 2) (3)

Where γ > 0.

Sigmoid Function: It is more relevant particularly in cases of the neural network based classifiers when they are not significant.

k(x,y) = tanh(αxTy + c) (4)

3.2 Analyzing Image dataset using customized CNN Models

Three models are customized based on Convolution neural network. Using archi-tecture of ResNet50 and VGG16 and their indigenous feature extraction capabilities, two classifiers are trained. In total five classifiers are trained using the image data-base of skin image dataset. The same models are trained and their performance ma-trix are obtained and evaluated.All five models are trained over image dataset con-taining training set consists of 10,664 malignant images and 9601 benign images The training set consists of 2666 malignant images and 2400 benign images of dimension 250x250. The parameters of these five models are as per Table-1.

Dimensionality reduction is applied on image dataset and all models are based on dimensionality reduction. The image dimensions are reduced to 224x224, augmented with zoom value 0.3, vertical flip and reshaped scale of 1/0.255. Activation function ReLu, optimizer Adam and sigmoid function is used at output layer since the output is of binary classification.

Table 1. Design and architecture of seven Models

Parameters	Model-1	Model-2	Model-3	Model-4	Model-5
Model Type:	Customized	Customized	Customized	VGG16	ResNet50
Epochs:	15	25	25	25	25, 50 and 100
Batch-Size:	64	64	64	32	64
Dimension:	224x224	224x224	224x224	224x224	224x224
Convolution Blocks:	02 with 02 layers	03 with 02 layers	03 with 02 layers	04 with total 13 layers	Pre-trained model weights with 50 layers including input and output layers.
Filters	16 and 32	16 ,32 and 64	16 ,32 and 64	64,128, 256, 512,512	
Pooling:	Maxpool	Maxpool	Maxpool	Maxpool	
Hidden Layers:	02	02	03	02 with 1028 nodes	
Activation Function:	ReLu	ReLu	ReLu	ReLu	ReLu
Optimizer:	Adam	Adam	Adam	Adam	Adam
Output Layer Activation Function	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Softmax

IV. OBSERVATIONS

Support Vector based classifier model was trained and tested over training and testing dataset respectively. Four folds of the dataset are created and using four di-verse kernels they were trained separately. Using the testing dataset of all four folds the models were tested separately using four diverse kernels (Linear, Polynomial, Radial Basis Function and Sigmoid). Mean value is obtained from the Performance matrix obtained using confusion matrix for all four folds as depicted in Table-2.

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Table 2. Design and architecture of seven Models

Kernel Type	Precision	Sensitivity	Specificity	Accuracy
Linear	0.9283	0.9903	0.8724	0.9474
Polynomial	0.9272	1.0000	0.8941	0.9532
RBF	0.9091	0.9901	0.8571	0.9367
Sigmoid	0.5191	0.4876	0.0000	0.3376

To analyze and evaluate the performance of SVM based models using four kernels apart from Accuracy other measures are observed using F1-score, Jaccard-score and Area Under Curve(AUC) are also obtained as depicted in Table-3.

Table 3. Performance measures for SVM models using four diverse kernels

Kernel Type	F1-score	Jaccard-score	AUC	Accuracy
Linear	0.9476	0.9473	0.9981	0.9474
Polynomial	0.9537	0.9532	0.9992	0.9532
RBF	0.9365	0.9365	0.9823	0.9367
Sigmoid	0.3173	0.3173	0.9964	0.3376

Considering the CNN based models, the three customized models are observed are compared using the performance measures obtained from confusion matrix. Cus-tomized three models are trained and tested with a batch size of 64. ModelCheck-point callback is used for all three models store the weights of respective models dur-ing the epochs. Another Early-Stopping callback is used to handle the issue of gener-alization gap issues.

Model-1 was iterated for 15 epochs while rest two models executed for 25 epochs. It uses two convolutional layers. The first layer and second layers used 16 filters of kernel size 3x3 and activation function ReLu(Rectified Linear Unit). Further it was followed by pooling layer using Maxpool layer of size 2x2 by dropout rate of 0.2. Following the flatten layer the fully connected layer consists of two hidden layers used 128 notes and 64 nodes in order used ReLu activation function and dropout rates 0.5 and 0.3 respectively. Output layer used sigmoid activation function since its binary type. The model was compiled using 'Adam' optimizer and 'Binary-cross Entropy' as loss function. The output matrix obtained in terms of confusion matrix and accuracy. Checkpoint was set using ModelCheckpoint to preserve the weights. ReduceLROnPlateau function was used to set the learning rate by passing attribute values that monitor validation loss for factor value 0.3 and verbose value 2.

Model-2 and Model-3 had some architectural differences compared to Model-1 in terms of numbers of convolution layers, size and numbers of filters and hidden layers as depicted in Table-1. Using the performance matrix obtained in terms of confusion matrix for all three models, accuracy, precision, Recall, specificity and sensitivity are obtained.

Table 4. Performance measures customized CNN models

Model	Accuracy	Precision	Recall	Specificity	Sensitivity
Model-1	82.29%	82.88%	82.33%	82.88%	85.35%
Model-2	80.68%	72.77%	89.72%	73.36%	89.72%
Model-3	81.76%	69.44%	92.93%	71.86%	92.93%

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Two other classifier models VGG16 and ResNet50 were trained using the training set and tested for 25 epochs. The VGG16 model consists of five convolution blocks and sixteen layers consecutively. At all layers used ReLu activation function, MaxPool and different numbers of filters, kernel size, pool-size and strides. The ResNet50 based classifier model used pre-trained weights to validate the test set. The classifier used to test validation dataset using initial weights used for kernel transfer learning.

V. PERFORMANCE ANALYSIS AND INTERPRETATION

Considering the performance of SVM based classifiers and CNN based three customized classifiers compared with the VGG16 based and ResNet50 based classifiers can be summarized as follows referring Table-2.

(i) Linear kernel based SVM classifier Accuracy is observed to be 94.74% highest among other three kernel based classifiers. However, the lowest accuracy 33.76% observed in case of sigmoid kernel based classifier. (Reference Table-2).

(ii) Considering the Precision, sensitivity and specificity performance shows that Linear kernel based SVM classifier performs the best among all classifiers and yield 92.83%, 99.03% and 87.24% respectively. Sigmoid based SVM classifier model perform poorly and yield 51.91%, 48.76% and 0.00% respectively.

(iii) F1-score and Jaccard-score are verifying the classifier performances obtained by analyzing the Accuracy, specificity, sensitivity and precision. The highest F1-score and Jaccard-score for Polynomial kernel based classifier is observed to be highest among all classifiers. However, the Linear based classifier is quite close to in performance compared to the Polynomial based classifier.

(iv) Comparing Customized CNN based classifiers performance shows that Model-1 classifier yields 82.29% accuracy which is highest among other two CNN based models. However Recall/sensitivity is 92.93% in case of Model-3 classifier but overall performance considering accuracy, precision, recall, specificity and sensitivity consistency is best in case of Model-1 among all other CNN based customized models.

(v) VGG16 based CNN model performance doesn't show significant performance at 25 epochs in case of training and validation accuracy. It is observed that the VGG16 based classifier was almost consistent and observed to be 58.35% high-est accuracy even when the model was trained using Adam optimizer and Bina-ry-cross entropy as loss function from 25 to 50 epochs. The model contained 139,506,497 trainable parameters.

(vi) ResNet50 based classifier shows improvement in accuracy when numbers of epochs increased till 25th epoch. Validation accuracy obtained at 25th epoch was 80.23%. However, it dropped down when number of epochs are increased. At 50th epoch the accuracy obtained was 75.67% and 71.81% at 100th epoch. Overfitting caused the drop in accuracy.

VI. CONCLUSION

(i) Comparing the SVM based models having features extracted from the image da-taset and the CNN based models, SVM classifier that used linear kernel was signifi-cantly high with 94.74% accuracy. The accuracy of Linear kernel based SVM classi-fier was crossed verified using Jaccard similarity score and F1-score obtained as 94.76% and 94.73% respectively. AUC observed for Linear kernel based SVM classi-fier obtained 99.81%.

(ii) Sigmoid based SVM classifier performed significantly low.

(iii) Among customized CNN based classifier, Model-1 performed with significantly higher accuracy at 15 epochs. The model can be tuned to improve the performance. Numbers of filters and stride size (kernel) can improve the performance. The batch_size can also be increased to obtain better model performance. Precision and Recall tradeoff and significant good harmonic mean is observed for all three custom-ized models. It is also observed that dimensionality reduction doesn't improve CNN based model performance.

(iv) Type-II error is better addressed in case of CNN based model-3. FNR observed as 7.07% in case of Model-3 CNN based classifier. However, Type-I error is not ad-dressed significantly in case of Model-3. CNN based classifier Model-1 is addressing Type-I and Type-II errors in balanced way compared to other two CNN based mod-els.

(v) GG16 based CNN classifier model observed poorly performed and yield signifi-cantly low accuracy and other performance matrix at 25th epoch. It shows under-fitting.

(vi) ResNet50 based CNN classifier reasonably better at 25 epochs but, at higher epochs the performance drastically downgrades. It shows that the ResNet50 based model performance behavior is due to overfitting problem.

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