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Skin Cancer Detection Using Texture Operators and Deep Learning Model

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Abstract— Skin cancer cell detection can be done by extracting the relevant texture features. It can be more cost effective method when the dataset size is not relatively large and complex. Traditionally deep learning models have been used for classification of images as predictions have a high accuracy, however time taken to train a deep learning model is higher compared to a texture operator based model. Certain features of the images are relevant for accurate classification of images, when the dataset is less complex. Hence, a texture operator based model is developed which extracts relevant features using Gray Level Co-occurrence Matrix (GLCM). Colour features are also extracted and the features are classified using Light Gradient Boosting Machine (LightGBM). The result of the model is compared with the predictions of a deep learning model. The results are in good matching with deep learning model results.

Keywords— Texture Operator, GLCM, DenseNet, LightGBM.

I. INTRODUCTION

Cancer is a disease which involves uncontrolled cellular growth and reproduction. It is a major cause of death which kills approximately 10 million people per year. Affected cells may present in tumour and propagate to other parts of the body. Early detection is mandatory in cancer treatment. It is essential to correctly discriminate between malignant and benign tumours for better clinical treatment.

Traditionally, statistics based techniques have been used for classification of low risk and high risk cancer despite the involvement of high dimensional medical data. In order to circumvent the drawbacks of conventional statistical methods, more recently image processing, artificial intelligence, deep learning etc. has been applied which uses various parameters such as text data, mammograms, cell images, cell radius for cancer detection followed by treatment.

Deep learning technique is a part of machine learning (ML) which employs probabilistic, statistical, and optimization methods which enables computers to learn from the data of past cases and to find out which are hard to recognise patterns from complex and noisy data sets. ML based algorithm enables the system ability to learn automatically and enhances the experience without being programmed in a detailed manner. Machine learning focuses the development of programs that must access data for learning. The learning process begins with the studying the data to establish a particular pattern in the data provided and to make reliable and better decisions in the future. The main objective is to facilitate systems to automatically learn and provide very good results without human involvement and accordingly alter the decisions.

This work focuses on, development of texture operator based model for detecting skin cancer. The texture operator extracts features relevant to the classification of various types of skin cancer cell. It will be more efficient compared to a deep learning model as only certain features are extracted. The time taken to extract features in a texture operator based model is less compared to the time taken to train a deep learning model. The results of the model are compared with the predictions of the DenseNet model.

II. LITERATURE SURVEY

Convolutional Neural Network (CNN) model is used to automatically detect the WBC cancer from bone microscopic image. It is better than random forests, decision trees, SVM models in terms of accuracy [1]. Various types of cancer such as Lung cancer, brain tumor and skin cancer are diagnosed from pathological images using CNN model [2-4]. Machine learning classification methods such as SVM, Naive Bayes technique is used to detect the oral cancer which has a very good precision [5]. Various available lung cancer detection algorithms are compared to find out the anomaly. Principal Component Analysis (PCA) is used for reducing the dimension and increase in accuracy of classification techniques can be observed [6]. Identification of important features of images helps doctors and technicians with more accurate diagnosis [7]. Cervical cancer cell detection based on deep convolution neural network using stochastic gradient descent and back-propagation. Also used SPFNetis for feature extraction showed that the proposed model gives accurate results [8]. An application based on android was developed which uses smart phone camera for detecting skin cancer. The MobileNet v2 and Faster R-CNN models are implemented for detection and MobileNet v2 was found to

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have a higher accuracy and larger training time [9]. Convolutional Neural Network (CNN) layers have been used to extract the features of the images. It follows more general approach to detect WBC cancer from bone marrow microscopic image [10]. Faster R-CNN with multiscale detection function has slightly a higher accuracy compared to Faster R-CNN with Multi Loss function [11]. Deep Learning approaches has high precision for binary image classification. However high number of false positives found during performance evaluation. Precision percentages are less for image classification and much less for object detection [12]. CNN with dropout layer is to avoid over-fitting and more layers hidden to the networks to avoid over-fitting problem used for binary skin cancer classification. Fully connected layer of two hidden layers are customized and more intensive studies should be used to broaden the solution [13]. Attempts were made to decrease the time consumed. 3D GAN model is used to decrease the time consumed for assessing the cancer cells in the human body parts. Accuracy level is very much low which shall be improved by K-Fold validations [14]. ROI morphology operations are used to improve classification [15]. New Circle Scanning Algorithm (CSA) for re-direction of cancer cells. Region Proposal Network to fetch object proposals of the cells, R-CNN determines if the RPN extracted the region of the cell is object or not. These hybrid methodologies gave higher precision but uses higher computational cost [16].

III. SYSTEM DESIGN

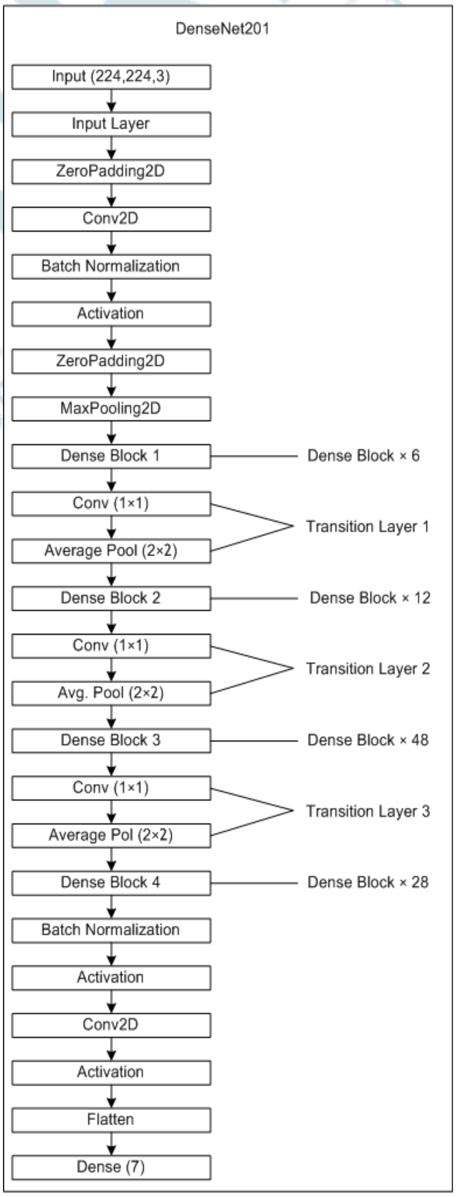
System is designed and developed to detect the cancer cells using deep learning and texture operator based model. The dataset HAM10000 is used as training data and it will be preprocessed using methods such as image scaling and gray scale transformations. Gray Level Co-occurrence Matrix (GLCM) is used as texture operator. The deep learning model which is used Dense Convolution Neural Network.

A. Dense Convolution Neural Network

Dense convolution neural network (DenseNet) is a type of deep learning model. To enable flow of information between various layers to have a collective knowledge, DenseNet concatenates its layers to its previous layers and the network becomes more compact and thin. It has a higher memory and computational efficiency. Since, DenseNet receives feature maps from previous layers with of various complexity levels and diversified features and it tends to give more smooth decision boundaries. The DenseNet model used in the project is DenseNet201 which has 201 layers.

A DenseNet model can be divided into two blocks, dense block and transition block. At first, the DenseNet contains an input layer which brings the image to the model for performing feature extraction and classification by subsequent layers. Then, a zero padding layer which adds zeroes to the image matrix to increase the size the matrix which ensures that the matrix does not shrink to a very small value after the convolution layers. After Zero Padding layer, a Convolution layer is present. Next, a batch normalization and an activation layer is present. Batch Normalization layer is used in deep learning models to solve internal covariate shift. The weights are changed in very mini batch hence the distribution of the network might change. Hence in Batch Normalization the weights are normalized in very mini batch.

After these layers in the beginning of the model a dense block is present. It consists of convolution, batch normalization, activation layer and a concatenation layer which is used to concatenate the previous block layer to the input of the dense block. Dense Block is followed by a transition block followed by another dense block and another transition block. There are 4 dense blocks in DenseNet201 and each of them runs for 6, 12, 42 and 28 times respectively. Transition block is used to reduce the layers by half. After the last dense block the layers are flatten and fully connected dense layer for classification.



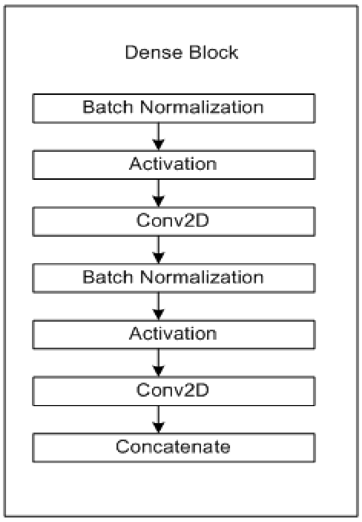


Fig. 1 The DenseNet201 model of the cancer cell detection application

B. Texture Operator

Gray Level Co-occurance Matrix: One of the main methods to characterize an image based on texture is the so-called Haralick Texture which is the quantification of the spatial variation of the grey tone values. The idea behind this is the joint probability distribution of grey level values and it is performed through the computation of the Gray Level Co-occurrence Matrix (GLCM). It generates the positions of the pixels which are having the similar gray level values. The main concept behind GLCM is adjacency of pixels in the image. It looks for nearby pixel pairs in a picture and records them over the entire image. The displacement vector $P_d[i, j]$ is calculated by adding up all the pairs of pixels with grey levels *i* and *j* that are separated by the *'d'*. The number of instances of the pixel values $n_{i,j}$ lying at a distance *'d'* in the image are represented by the formula GLCM $P_d[i,j] = n_{i.j.}$ The number of grey levels in the image n, determines the dimension of the co-occurrence matrix P_d, which is of the form n × n [17].

Colour Texture: Since GLCM requires a gray scale image to perform computation, the colour of the cancer cell image is not considered, hence mean and skewness of red, green and blue channels are extracted as colour features.

IV. PROPOSED METHODOLOGY

A deep learning and texture operator based model is created for the classification of the skin cancer cell images. In the deep learning model DenseNet201 is used and in the texture operator based model Gray Level Co-occurrence Matrix is used. Both the models have own advantages and disadvantages.

Since the dataset chosen is an imbalanced dataset, re-sampling of the dataset needs to be done as the model can be biased towards the majority class. To resample the dataset majority needs to be downscaled and the minority classes needs to be downscaled. Every class needs to have same number of data. In the proposed methodology, each class of dataset has 500 images after re-sampling. After re-sampling of the dataset image rescaling and gray scale conversion of the images needs to be done. The size of all the images is 224,224. The Image dataset is split into train and validation sets for training the model and to predict the validation accuracy respectively.

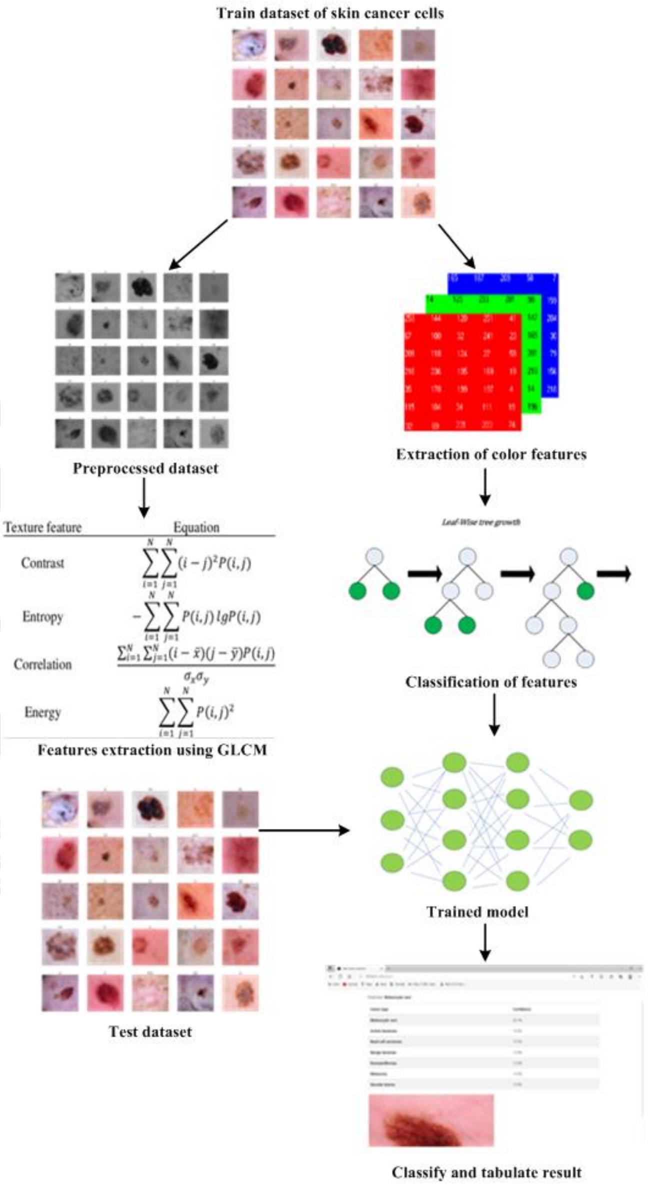


Fig. 2 Architecture of texture operator based model

In the deep learning model, the DenseNet201 takes pre-processed image as input and trains the model. Whereas in texture operator-based model the features are extracted using texture operator GLCM and colour features are used for classification using LightGBM. It is a gradient boosting framework that works on decision trees which aimed at increasing model efficiency while reducing the usage of the memory. A total 51 features were extracted. Among those features mean and skewness of the 3 colour channels are considered. Other features are extracted using the GLCM

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texture operator. GLCM has around 22 properties. Among them features extracted through GLCM are contrast, correlation, dissimilarity, homogeneity, and energy are extracted. Each of them extracts relevant texture information which can be used by the classifier for classification. Distances and the angles chosen for the GLCM matrix are 0, 1, 3, 5 and 0, π/4 and 3π/4. After training the model the results are plotted in the classification matrix and inferences are drawn. The model with the higher accuracy is linked to the user interface. The user interface will be used to take an image from the user to perform prediction based on the trained model and display the result to the user. It will display one of the 7 types of cancer. Inference can be drawn by knowing the type of cancer as among the types of cancer present in dataset only melanoma is malignant and rest types are benign.

V. RESULTS

The classification report of both the models are plotted to draw inferences from the models. The following table displays the obtained result. The following results are tabulated with the validation data.

Table 1 The tabulated results of the trained models

Models	Precision	Recall	f1-score
DenseNet201	0.80	0.80	0.79
Texture Operator based model	0.79	0.78	0.78

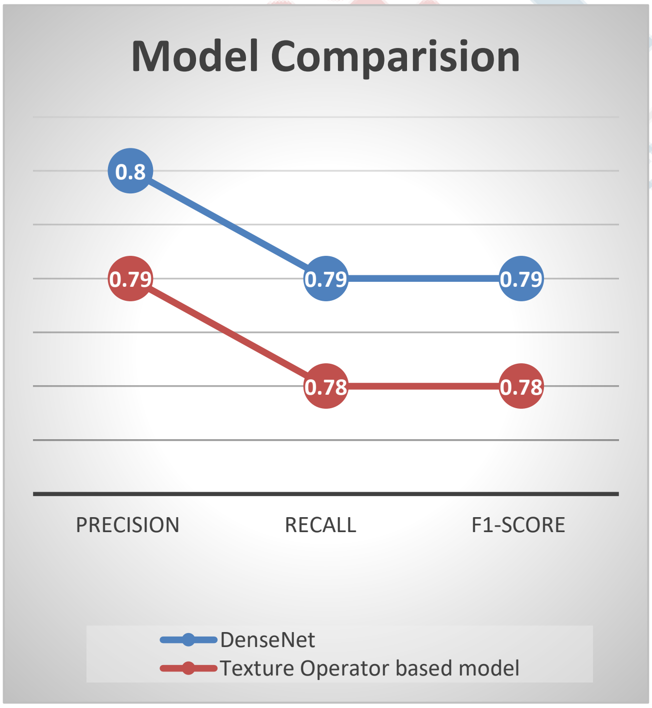

Fig.3 Classification models comparison

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Classification Report:
              precision    recall  f1-score   support

       akiec       0.92      0.78      0.84       126
         bcc       0.71      0.86      0.78       105
         bkl       0.61      0.55      0.58        95
          df       0.94      1.00      0.97       101
         mel       0.67      0.67      0.67        87
          nv       0.76      0.74      0.75        89
        vasc       0.95      1.00      0.97        97

    accuracy                           0.80       700
   macro avg       0.80      0.80      0.79       700
weighted avg       0.80      0.80      0.80       700
```

Fig. 4 Classification Report of DenseNet201 model

```
Classification Report:
              precision    recall  f1-score   support

       akiec       0.80      0.80      0.80       126
         bcc       0.79      0.71      0.75       105
         bkl       0.63      0.62      0.62        95
          df       0.92      0.97      0.95       101
         mel       0.61      0.75      0.67        87
          nv       0.76      0.64      0.70        89
        vasc       0.97      0.96      0.96        97

    accuracy                           0.78       700
   macro avg       0.78      0.78      0.78       700
weighted avg       0.79      0.78      0.78       700
```

Fig. 5 Classification Report of Texture Operator based model

Both the models do not have much difference in its performance parameters. Deep learning can still give much better performance when the dataset is larger with many classes and can extract more features as opposed to the texture operator based model. Texture operator based model can give good precision when the dataset is small and the number of classes is less. The result also proves that texture operator based model has extracted the relevant texture features of the cancer cell image hence the model has a precision which is close to a deep learning model.

VI. CONCLUSION AND FUTURE WORK

Both the models have advantages and disadvantages. Texture operator based model can be used for a smaller dataset with less number of classes, but as the complexity of the data along with size of the dataset and its classes increases more features needs to extracted in that scenario a deep learning model would be appropriate.

Further work can be done with respect to texture operator-based model to extract more relevant features with respect to the skin cancer cell. Other properties in case of GLCM would extract features which may result in accurate classification. More features which differentiate the different types of cell can be defined.

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