Artificial Intelligence Based Real-Time Skin Cancer Detection

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Prof. T. Kishore Kumar
Department of ECE
National Institute of Technology Warangal
Warangal, India
kishoret@nitw.ac.in

I. Naga Himanshu
Department of ECE
National Institute of Technology Warangal
Warangal, India
nagahimanshu11@gmail.com

***Abstract*—Skin cancer emerge as the one of the most dangerous kinds of cancer occurred to human beings. Early detection of skin cancer is curable and necessary treatment can save the patient's life. There are several types of skin cancer diseases with each having respective characteristics. The traditional way of detecting skin lesion include ABCDET technique which is widely used by the doctors. However manual detection of skin lesion fails in the current era with rapidly increasing skin cancer cases world-wide. Automatic detection of skin lesion is needed to perform the detection faster and minimize the diagnostic errors, lowering the overhead on the doctors. With the advent of different machine learning and deep learning techniques, an intelligent system can be developed to identify the skin lesions accurately. Neural networks are such a deep learning models used for the extraction and classification of skin lesion features. This paper presents a comparative analysis of skin lesion classification using CNN and Random Forest classifiers and real-time simulation of skin cancer detection. The dataset considered is HAM10000 dataset which provides a wide range of images of seven different types of skin lesions. Followed by image preprocessing for denoising and artifacts removal, image segmentation is done using Active Contours Without Edges (ACWE) and feature extraction is done using ABCDT technique where the textural analysis is implemented using Gray Level Co-Occurrence Matrix (GLCM) and Fractal Dimension texture analysis (FDTA). The accuracy with CNN classification is obtained to be 91.97% and that of Random Forest classification is 89.82%. The real-time simulation for skin cancer detection using trained models is performed and CNN model performed well than Random Forest classifier.**

Keywords—skin lesion, ABCDT, ACWE, GLCM, FDTA, CNN, random forest

I. INTRODUCTION

In the current scenario of unpleasant environmental conditions, humans are subjected to different kinds of skin infections. High exposure to Ultraviolet (UV) light can cause damage to DNA in skin and forms abnormal cells that lead to skin cancer. The lesion is treated to malignant which is most dangerous if the lesion region rapidly grows and spreads over other parts of the skin. It can be cured by excising the lesion area through surgical operation. On contrary, benign lesions develop over the area but do not spread rapidly and hence are not much dangerous. Medical attention is utmost important while in early stages of tumor to lower the mortality rate. Malignant skin cancer includes skin cancer types such as actinic keratoses and intraepithelial carcinoma (akiec), basal cell carcinoma (bcc), melanoma (mel) whereas benign skin cancer types include benign keratosislike (bkl), dermatofibroma (df), melanocytic nevi (nv) and vascular lesions (vasc). If the tumor is left unchecked, this can become deadly by affecting other body tissues and organs. Detection of skin cancer in beginning phases can significantly prevent mortality.

Two conventional methods of identifying skin cancer include Biopsy and Dermoscopy. Biopsy is an invasive method in which the skin cancer sample is excised from the body and provided to lab-testing. The results will be determined after the respective lab tests, which will require more time for the interpretation of skin cancer. On the other hand, Dermoscopy is a non-invasive method of identifying skin cancer using magnified lens and determine the result of skin cancer. It requires keen observation of skin lesion through magnifying lens and doctors use ABCDE method for the interpretation of the skin lesion. This process is also time consuming as it requires detailed understanding and observation of the skin lesion by the doctors. When number of patients increase, the time-consuming conventional methods fail to determine the skin cancer of the patient within less time. Hence there is a need to replace manual detection of skin cancer with auto-diagnostic methods.

The role of AI is highly appreciated as it can reduce the overhead on doctors to keenly observe and interpret the results. Deep learning models such as Convolutional Neural Networks can be used to identify skin cancer using image classification. Introduction of such types of machine learning and deep learning models into medical field results in advancements of the field as well reduce the diagnostic error rate.

II. LITERATURE SURVEY

H. Alquran et al. [4], developed a melanoma classification system using SVM classifier with Otsu's thresholding, followed by ABCD feature extraction and Gray Level Co-occurrence Matrix (GLCM). Principal component analysis (PCA) is done for the purpose of feature selection. The results obtained to be the classification accuracy of 92.1%.

M. Vidya and M. V. Karki [6], proposed a benign vs melanoma skin lesion classifier wherein the algorithm applies feature extraction using ABCD rule, GLCM and HOG feature extraction. Geodesic Active Contour (GAC) technique, an active contour technique was used for image segmentation. The classification was done using SVM, KNN and Naïve Bayes classifier, where the SVM classifier outperformed with an accuracy of 97.8%.

Reference [8] provided a comparative analysis on classification of skin lesions using KNN, Decision tree and SVM classifiers. In preprocessing phase, the hair removal was done using Dull Razor algorithm. As image segmentation step, mean-shift image segmentation algorithm was used and ABCD feature extraction technique was used on the dermoscopic images. The features are selected based on Relief algorithm and are classified using the classifiers. The highest accuracy turned to be 78.2% with SVM classifier.

In [9], the authors proposed an automatic skin lesion segmentation method in which preprocessing for noise and hair removal is performed in the first phase, followed by image segmentation using GrabCut and Flood fill algorithms. Classification of skin lesions is done by k-means clustering. The proposed method was tested on ISIC 2017 and PH^2 datasets, resulted in accuracy of 92% and 96% respectively. The Dice coefficient values are obtained to be of 0.82 for ISIC 2017 dataset and 0.92 PH^2.

III. Design Methodology

The design methodology as shown in "Fig. 1", includes the following steps: HAM10000 dataset collection and preprocessing, Image preprocessing, Active Contour Without Edges image segmentation, Feature extraction and feature classification. The classification is done using CNN and Random Forest classifiers. The trained classifiers are eventually simulated for real-time performance in detection of skin cancer.

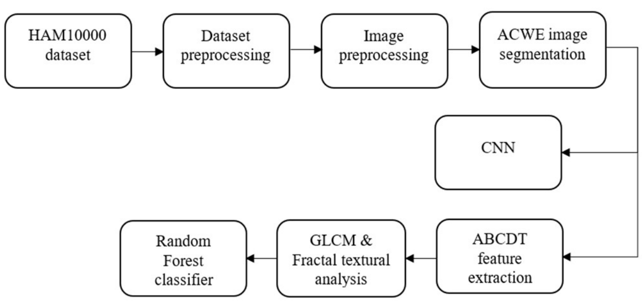

Fig. 1. Design methodology.

IV. Dataset

A. Dataset Collection

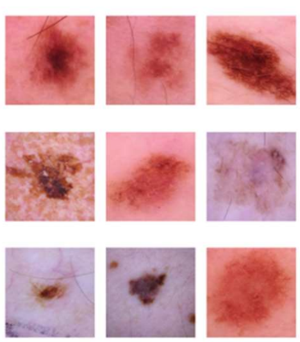

Fig. 2. Sample images from HAM10000 dataset.

The dataset used in this project is the HAM10000 dataset. It consists of 10015 skin lesion images of seven different skin cancer types (akiec, bcc, bkl, df, mel, nv, vasc). It is collected from Harvard Dataverse which was originally deposited by the Department of Dermatology of the Medical University of Vienna, and the skin cancer practice of Cliff Rosendahl in Queensland [1]. Sample images from the dataset are shown in "Fig. 2".

B. Dataset Preprocessing

The HAM10000 dataset is imbalanced and biased with a greater number of *nv* skin lesion images comprising 60% of the dataset than the remaining six skin lesions. The problem of imbalanced data can be addressed using different approaches such as Random sampling, Cost-Sensitive methods, Kernel-based methods, Synthetic Minority Oversampling Technique (SMOTE), [14]. Data Augmentation is the process referred to as applying image transformations on raw input data to produce new data. It generates new data by applying transformations such as rotation, flip, offset etc., on raw data hence balancing the dataset. In addition to data augmentation, random oversampling is done to balance the dataset with even number of entries of different skin lesion types. Another advantage of training the model with augmented data is that, the model is robust to different conditions of input image, which is necessary for real-time operations. It can be illustrated as in "Fig. 3".

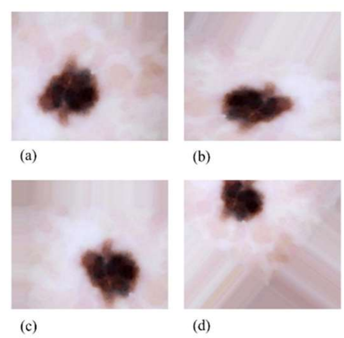

Fig. 3. Data Augmentation results (a) Original image, (b), (c), (d) Data augmented images.

V. Image Preprocessing

As image preprocessing step, it is necessary to eliminate the noise and artifacts such as hair, veins from the skin lesion image [9]. These can intervene the training phase and deviate the model from accurate training. It can be performed by using appropriate filters and image morphological operations.

A. Filtering

Denoising can be done using image filtering techniques such as Averaging filtering, Median filtering, Gaussian filtering, etc. In addition in providing excellent noise-reduction capabilities and considerably less blurring with same filter size as of linear smoothing filters, Median filters preserves the edge information of the image, as in [2].

B. Hair Removal

The artifacts like hair can be removed by applying Blackhat morphological operation. It extracts dark objects of interest on a bright background. It is obtained as the difference between closing of input image and the input image as in “(1)”.

$$B_{hat}(u) = u \bullet b - u \tag{1}$$

where $B_{hat}(.)$ is the blackhat transform, b is the blackhat kernel and u is the input image. The hair removal results are illustrated in “Fig. 4”.

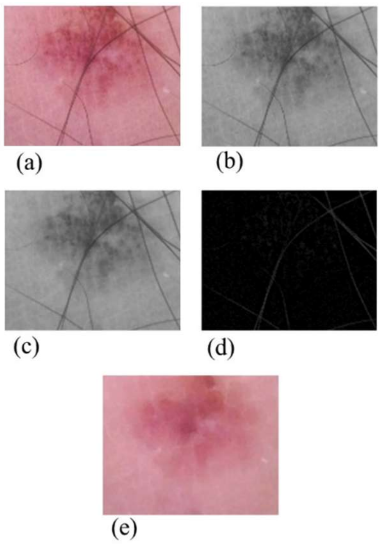

Fig. 4. Image preprocessing results (a) Original image, (b) Grayscale image, (c) Median blur image, (d) Blackhat operation, (e) Final preprocessed image.

VI. Image Segmentation Using Active Contours Without Edges (ACWE)

Image segmentation is the process of extracting the Region of Interest (ROI) (i.e., skin lesion) from the input image. Different image segmentation approaches include Meanshift segmentation [8], Active contour segmentation [7], Otsu thresholding, Region-based segmentation, Watershed algorithm etc. The segmentation of the skin lesions is performed using Active Contours Without Edges (ACWE) method [13].

The intuition behind active contours is the evolution of the boundary curve that utilizes energy and force constraints to obtain the ROI. The active contour segmentation techniques include Snake model, Gradient Vector Flow model, Balloon model, Geosedic Active contour model [7]. The Active Contour Without Edges technique, developed by Chan and Vese [13], is based on Mumford-Shah segmentation and level set formulation. The active contour model is represented as of “(2)”.

$$J(C) = \int_C E_{internal}\big(C(s)\big)\, ds + \int_C E_{external}\big(C(s)\big)\, ds \tag{2}$$

The contour energy is the sum of internal energy (representing the elasticity and smoothness of the contour) and external energy (energy of contour towards the object in the image). In this technique, the contour energy is minimized by treating it as minimal partition problem. After applying level set formulation, it reduces to a ”mean-curvature flow”-like evolving active contour which then vanishes at the desired boundary. This method, unlike other proposed active contour segmentation techniques, does not rely on the edge function and the image gradient to halt the curve evolution, and hence it can be applied to segment the objects whose boundaries are not well-defined by the gradients. The results of image segmentation using this method is illustrated in “Fig 5”.

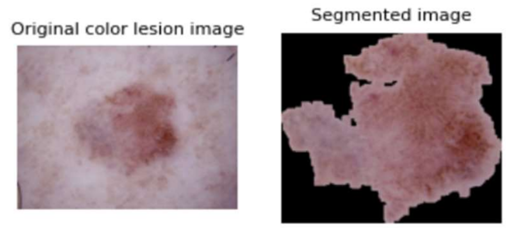

Fig. 5. Image segmentation using ACWE.

VII. Feature Extraction

This phase requires accurate extraction of features from the skin lesion image. Different characterizable features of skin lesion include border, color, texture. The most prominent technique utilized for identifying features of skin lesion include ABCDT diagnosis technique. In this work, The textural analysis is performed using Gray Level Co-Occurrence Matrix (GLCM) and Fractal Dimension Texture Analysis (FDTA).

A. ABCD (Asymmetry, Border, Color, Diameter)

ABCDT technique is used to extract the features from the skin lesions. It stands for Asymmetry (A), Border irregularity (B), Color (C), Diameter (D), Texture (T).

- **Asymmetry**: In general, the skin cancer lesions are asymmetrical when compared to symmetrical skin lesions such as moles. The asymmetry test is done on horizontal and vertical axes and qualitatively identified as skin cancer if the lesion is asymmetrical.
- **Border**: Non-cancerous models have smooth and even border whereas melanoma borders are irregular.
- **Color variation**: Color is one of the prominent characteristics of skin lesion. Skin lesions possess different intensities of red, green and blue components which tend to a particular skin cancer, for e.g., *akiec* has reddish brown color, *mel* has blackish brown color, *nv* has dark brown color whereas *vasc* are purple or pink.
- **Diameter**: If the diameter of the skin lesion exceeds 6mm, the lesion is considered to be cancerous.

B. Gray Level Co-Occurrence Matrix (GLCM)

Haralick et.al. [11], developed textural analysis technique based on gray spatial dependencies, named as Gray Level Co-occurrence Matrices (GLCM). It gained wide importance in the field of textural analysis for its derived features. It characterizes the texture of image by quantifying the relationship of the pixel pairs of the image. GLCM produces twenty-eight features, of which four features namely Contrast, Correlation, Entropy, Homogeneity are of interest. The contrast is characterized by the Standard deviation of the image, Entropy measures the randomness present in the image. Homogeneity measures the consistency of pixel intensity values.

C. Fractal Dimension Textural Analysis (FDTA)

Fractals originate from chaos concepts of mathematics. They exhibit self-similarity property where gradually diminishing similar patterns are created. These are produced by a regenerative feedback process which produces infinite number of patterns. Fractal dimension is an important characteristic that holds the information of geometric structure. As of reference [12], the fractal dimension can be calculated as "(3)".

$$D = log_{\frac{1}{r}}(N_r) \quad (3)$$

where N_r refers to the distinct non-overlapping copies of N when it is diminished by a ratio r. The fractal dimension quantifies the roughness of the image which progressively increases with its roughness texture. With respect to the skin lesions, the roughness varies with all types of skin cancer like the *akiec*, *nv* have rough texture when compared to *vasc* lesions.

VIII. Results and Discussions

A. Classification Using CNNs

The CNN model was built using Tensorflow 'v2.10.0' library. In order to obtain data augmentation, the CNN model is preceded with data augmentation layers such as Resizing, Rescaling, Random Rotation, Random flip and Random zoom. This enables the images to be augmented on the fly during training instead generating batchwise. The classification accuracy obtained to be 90.72% for training and 91.97% for validation phase. After training, the model is subjected to real-time simulation for prediction of random skin cancer images. The simulation is performed using OpenCV and the images are displayed through mobile phone for instance. The results are obtained as illustrated in "Fig 6". In the simulation, the CNN model displayed a detection hit ratio of 90%, as if 9 out of 10 images are detected accurately.

Fig. 6. Real-time simulation of skin cancer detection using CNNs.

B. Classification Using Random Forest

The data consisting of ABCD, GLCM, FDTA derived features is subjected to RBF kernel approximation and is fit to the Random Forest classifier. The confusion matrix obtained is as shown in "Fig 7". The accuracy is obtained as 89.82%. Despite of better accuracy, the Random Forest classifier exhibited a hit ratio of 50% in real-time simulation.

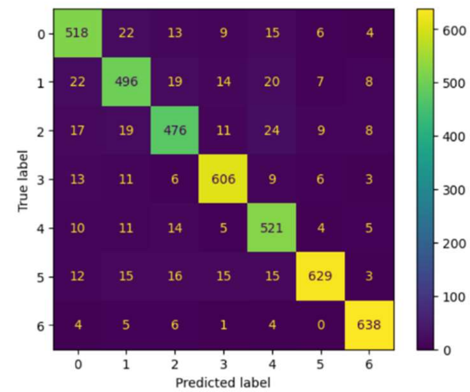

Fig. 7. Confusion Matrix obtained from Random Forest classification.

IX. Conclusions and Future Work

In this work, the seven types of skin lesions provided by HAM10000 dataset are classified using CNN and Random Forest classifiers. Accuracies of 91.97% and 89.82% are achieved using CNNs and Random Forest classifiers respectively. The classifiers are subjected to real-time simulation using OpenCV. The CNN model performed well in detecting the seven types of skin cancer with better accuracy than the Random Forest classifier. The detection latency using the CNN model is significantly high thereby lowering the throughput. Real-time object detection algorithms combined with active contour snakes will greatly improve the performance, optimal for real-time embedded systems. This model can be deployed onto a microcontroller interfaced with a high resolution camera and can be directly utilized by the doctors in skin cancer diagnosis with ease.

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