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Skin disease detection and classification using different segmentation and classification techniques

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Abstract - *Skin diseases are common and affect a large population all over the world. Skin disease management necessitates accurate diagnosis and treatment. The systems used image processing and machine learning techniques to automate the process of identifying skin diseases. With the advancement of machine learning algorithms, automated systems for skin disease detection and classification are now possible. This paper presents a study and exploration of various segmentation techniques used to detect the type of skin lesions, including Region-based segmentation, Otsu's Thresholding, Boundary, and spot detection, and Entropy-based segmentation. Furthermore, support vector machines, Decision Trees, Random Forests have been used to classify skin diseases. Melanotic nevi, Melanoma Benign, Keratosis, Basal cell Carcinoma, Actinic Keratosis, Vascular Lesions, and Dermatofibroma are the seven types of skin cancer. The primary goal of this project is to improve diagnostic system accuracy by utilizing image segmentation and classification techniques.*

***Key Words*: Skin Disease Classification, Convolution Neural Network, Deep Learning, Classification Algorithms, Image Processing.**

1. INTRODUCTION

The early diagnosis and treatment of skin illnesses depend greatly on the detection and classification of skin diseases, which is a critical responsibility in dermatology. Skin conditions are common around the world, and early diagnosis and classification can prevent death and lessen the financial load on the healthcare system. Recent advancements in machine learning and computer vision have led to the development of automated systems for skin disease detection and classification, which can assist dermatologists in providing accurate diagnoses and individualized treatments.

The epidermis, dermis, and subcutaneous tissue make up the skin, which is the largest organ in the human body. The epidermis is the skin's outermost layer and a barrier against environmental hazards. Layers of keratinocytes, melanocytes, and Langerhans cells make up its structure. Keratin, which is synthesized by the skin's keratinocytes, gives the skin its strength and ability to repel water. Melanin is a pigment made by melanocytes that give skin its color and shield it from the sun's UV rays.

The dermis is the skin's intermediate layer and contains connective tissue, blood vessels, nerves, and other structures. It provides structural support to the skin and contains collagen and elastin fibers, which impart elasticity and strength to the skin. There are also hair follicles, perspiration glands, and sebaceous glands.

Fat and connective tissue make up the subcutaneous tissue, the skin's deepest layer. It Insulates and regulates body temperature.

Although cancer can manifest itself in any of the skin's layers, basal cell carcinoma (BCC), the most prevalent form of skin cancer, is most often found in the epidermis' basal cells. The epidermis's base is home to a special type of cell called a basal cell. The epidermis' outermost layers are frequently the starting point for squamous cell carcinoma (SCC), another frequently encountered form of skin cancer. Melanoma, a more aggressive form of skin cancer, develops in the melanocytes, which are in the epidermis's deeper layers. Depending on their form and cause, skin lesions can also affect various layers of skin. For instance, psoriasis lesions, which are characterized by thick, scaly regions of skin, affect the epidermis, and can extend into the dermis. In severe cases, the subcutaneous tissue may be affected by eczema lesions, which are caused by inflammation and irritation of the skin.

The purpose of this work is to provide a comprehensive analysis of existing methods and algorithms for detecting and classifying skin diseases. The HAM10000 dataset, which contains photos of skin lesions, will be used to test the effectiveness of various methods and algorithms. We hope that the work presented here will help move the field of skin disease identification and categorization forward and ultimately improve the lives of many people around the world.

In this work, we employ the publicly available HAM10000 dataset for machine learning. Ten thousand and fifteen dermatoscopy photographs of pigmented skin lesions are included, with seven thousand two hundred and ninety-five representing benign lesions and two thousand depicting

malignant melanomas. Lesions such as seborrheic keratosis and angiomatosis make up the remaining 715 photos. In addition to the images themselves, the collection contains descriptive information about them, such as the patient's age and gender, the anatomical location of the lesion, and the diagnosis. In it, you will find examples of both benign and malignant skin lesions. Below are the seven classes of skin diseases present in the HAM 10000 dataset.

Moles or melanocytic nevi (nv), are benign skin growths made up of melanocytes, which are epidermal cells responsible for creating pigment.

Melanoma (*mel)* is the malignant skin cancer which occurs because of the melanocytes that is the pigment-producing cells of the epidermis.

Lesions that mimic seborrheic keratosis or solar lentigines, which are benign skin growths, are known as *keratosis-like lesions (bkl).*

Cancer of the basal cells of the epidermis, also known as *basal cell carcinoma (bcc)*, manifests as a firm, pink, or pearly white nodule on the skin.

Actinic keratoses (akiec) are the premalignant skin lesions that, if untreated, can develop into squamous cell carcinoma. They are typically brought on by prolonged sun exposure.

Blood vessel abnormalities such as angiomas, angiokeratomas, and pyogenic granulomas are referred to as *Vascular lesions (vas).*

A benign skin growth known as a *dermatofibroma (df)* typically presents as a tiny, hard bump.

Cancer of the epidermis or other melanocyte-containing tissues, known as melanoma, begins in these cells. A black, asymmetrical lesion on the skin is one possible manifestation. Different layers of skin are affected by each of these blemish's kinds.

Epidermis lesions such as melanocytic nevi and seborrheic keratosis are more common than those caused by basal cell and squamous cell carcinomas, which can affect both the epidermis and the higher dermal layers. Skin's dermis and subcutaneous tissue are not immune to melanoma's reach. The affected skin layers might also be affected by the location and severity of the lesion.

2. LITERATURE SURVEY

[1] Here the authors have used SVM as a machine learning algorithm to focus on Melanoma and Carcinoma. The authors of this paper aimed to create an automated system that can assist dermatologists in determining whether a skin lesion is benign or malignant, which is useful in the early detection of Melanoma. They trained and tested their SVM-based classification system on 1,032 skin lesion images in their study and extracted relevant features from the images using image processing techniques such as normalization, segmentation, and feature extraction. The extracted features were then used to train the SVM classifier, which achieved an accuracy rate of 95.8%.

[2] In this paper the authors have investigated the efficacy of different machine-learning algorithms for classifying skin diseases using color and texture features extracted from images. The authors gathered a collection of skin disease images from various sources and preprocessed them to extract color and texture features. The image dataset consists of Chronic Eczema, Lichen, and Plaque psoriasis images captured with a digital camera and processed to extract Red, Green, and Blue (RGB) color features and Gray Level Co-occurrence Matrix (GLCM) texture features. To compare classifier performance, different combinations of features with four popular ML algorithms were considered. Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) had the highest classification accuracy of the four algorithms tested. The paper concludes that machine learning algorithms can be effective tools for classifying skin diseases and that the algorithm chosen should be based on the specific features of the disease being diagnosed. The study's results show that LDA performed better in binary and multi-class scenarios using color feature-based classification, SVM performed better for texture features in both binary and multi-class classifiers, and LDA and SVM classifiers performed better in binary and multi-class classification for the combined feature.

[3] In this paper the authors did a literature review to compare how different image-processing techniques can detect and classify psoriasis diseases. The goal of the authors was to look at the current research in this area and compare how well different methods work for finding and classifying psoriasis from images of skin. The review found that different image processing methods, such as texture analysis, feature extraction, and machine learning algorithms, have been used to find and classify psoriasis. Texture analysis has been used to look at how the skin of psoriasis lesions feels, and feature extraction techniques have been used to pull out things like color, shape, and texture from images of skin. Psoriasis has been put into groups using machine learning algorithms like support vector machines (SVMs), artificial neural networks (ANNs), and random forests (RFs). The machine learning algorithms have shown promise in correctly classifying psoriasis lesions, with SVMs being the most used algorithm in the literature.

[4] Here they offered an overview of the different techniques and methods used to find and categorize skin diseases. Using Image Processing and classification techniques, the main goal of this project was to make diagnostic systems more accurate. In the system that is being proposed, an image captured by a camera is used as input. By using Contrast Enhancement and

Grayscale Conversion, this image will be prepared for segmentation. The Global Thresholding technique is used to divide the image that has already been processed into sections. This is how the real affected area is found. Using Grey Level Co-occurrence Matrix, texture features like Energy, Entropy, Contrast, and IDM (Inverse Difference Moment) are taken from a segmented image. Image Quality Assessment features are taken out, such as Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). Using the Decision tree technique, the extracted texture features will be used to find skin diseases and classify them as melanoma, leprosy, or eczema if they are found. This system uses pictures of the skin taken by a camera to figure out if it is healthy or not. If it isn't healthy, it is categorized as Melanoma, Eczema, or Leprosy.

[5]Here the authors gave a method for deciding whether skin cancer in two different moles is benign or malignant. At first, the dataset has images of two different kinds of moles that are mixed. These images have already been changed so that they can be used for classification. When the pre-processing of the dataset is done, these images are sent to CNN models like VGG16, VGG19, and Inception V3 to pull out the characteristics. Lastly, these images are sent to different machine-learning classifiers to figure out if the moles are harmless or dangerous. The results show that the Inception V3 model with the neural network classifier has the best accuracy at 83.2%.

[6] In this work they have used features such as entropy, variance, and maximum histogram value of Hue-Saturation-Value (HSV). These characteristics are used to construct a machine learning algorithm using Decision Tree (DT) and Support Vector Machine (SVM). Accuracy is used to evaluate the proposed algorithm's performance. The first phase includes image processing for skin disease detection, and the second phase includes a machine-learning algorithm. Because of changes in the skin's characteristic features such as color and texture, it is difficult to diagnose skin disease in the primary and other stages. SVM color features produce 8% better results. As a result, the decision tree produces better results. The color of various skin diseases is nearly identical. It makes classification difficult. As a result, texture features produce better results.

[7] Here they have thoroughly examined how texture-based feature extraction can be used to find skin diseases and suggest a system based on what they found. In this paper, they worked on texture-based features derived from the GLCM matrix that are used to find skin diseases is discussed and consolidated. Most of the work is done to find skin cancer, but some of the works also look at other diseases like psoriasis, warts, moles, and eczema. Classifiers like neural networks and SVM decide whether an image shows a disease or not. Most of the research shows an overall accuracy of 90% or higher. Contrast, Correlation, Energy, Entropy, and Homogeneity are the top five features used in all this work.

3. METHODOLOGY

In the proposed system we start with the basic image processing techniques with a smaller dataset and then as we move ahead, we work on multiple images and proceed towards the exploration of segmentation techniques. Thereafter we have worked on the complete HAM10000 dataset, using different ML techniques. Furthermore, to increase the efficiency of the model CNN was used and finalized.

3.1 Basic Thresholding

The first algorithm developed by us is basic thresholding. This type of thresholding technique is based on pixel intensities, if the pixel intensity is greater than the specified threshold it would be considered as one or vice versa. Thus, converted into binary image. It is one of the basic algorithms used to detect whether the skin disease is present or not. For this thresholding algorithm, we uploaded the image from our dataset in the model and a basic classification of the image (disease detected or disease not detected) was done. Initially, the image is passed through gaussian filter so that other insignificant parts would become blur and then the thresholding algorithm was applied on basis of term percentage.

3.2 Entropy based thresholding

In Entropy based thresholding algorithm, the optimum thresholding value is acquired using the maximum entropy plotted on the histogram and by choosing that respective pixel intensity and applying the thresholding technique on it and acquiring the results.

In Entropy based thresholding, a histogram is plotted to obtain the frequency of gray levels in an image and then cumulative sum of the histogram was obtained and is normalized. After that, initialization of threshold value and maximum entropy is done, and the model is made to iterate through all the possible values where probabilities of two parts were been calculated. Then, the maximum entropy of two parts was calculated by applying the equations:

entropy1 = -p1 * np.log2(p1) if p1 > 0 else 0 ...*3.2.1*

entropy2 = -p2 * np.log2(p2) if p2 > 0 else 0 ...*3.2.2*

After taking into consideration, the total entropy obtained by adding both the results of above equations.

The parameters were updated i.e., threshold value and maximum entropy based on current entropy. While implementing it, If the current entropy is higher than the parameters mentioned, then the entropy would be updated or vice versa. And finally, the thresholding was performed on the image and the desired results were obtained.

3.3 Boundary and spot detection

In this method, we have defined a function in which it would check if the spot is a disease or not by defining the region of interest. If the spot falls within the region of interest it would return true or vice versa. Initially the same steps were followed as done in the above algorithms such as converting the image to grayscale and applying gaussian filter on an image and then the Otsu thresholding algorithm was applied to segment the image and then the contours were made to search in the thresholder image and thus, the contours were drawn on the original image. The track of true positive, false positive, and false negative spots was kept. Then after loop over the contours were developed in which if the area was less than a certain threshold, it was a spot. For accuracy, it was made to check if the spot was true positive or false positive. Thus, the desired results were achieved.

3.4 Otsu based Thresholding

Initially, the image is uploaded from the dataset and the image is converted to grayscale and the gaussian filter is applied to reduce the noise and finally, the binary thresholding and Otsu thresholding is applied on the image and the ground tooth labels for the image were provided. Thus, we obtained the predicted labels from the thresholded image and acquired the desired results.

3.5 Decision Tree

After importing the dataset, preprocessing is done using Label Encoder to convert into categorical data for classify the images into multiple classes and the decision tree classifier is given to the model. By using train and test split, dataset was trained and tested and finally, the results were displayed using the confusion matrix.

3.6 Support Vector Machine Algorithm

In support Vector Machine, the image is classified using three kernels namely linear, poly and rbf (Radial Basis Function). The kernels transform the non-linearly separable dataset to a linearly separable dataset. In this method, hyperplane is used to classify the images into different classes. The most accurate results were given rbf kernel in compared to linear and poly kernel with random state as 42. The data was then trained and fitted to the model. Thus the confusion matrix was plotted as a result.

3.7 Random Forest

After importing the dataset, the random forest classifier is given to the model comprising of 100 decision trees and random state as 42, so that it would take the same set of datasets each time it is run. Thus, using train, test split the model is trained and using fit, the trained data is fitted to the model. Thus, the model is tested using test dataset and the desired results were obtained.

3.8 Deep Neural Networks

As HAM10000 is a huge dataset, with different supervised algorithms we realized that it is essential to proceed towards neural networks. Neural network possesses the capability of processing complex computations, handling huge data, and end to end automation. We initially worked on preprocessing dataset and thus the preprocessed data was fed to deep neural network with 10,000 input images as neurons to an input layer, with two hidden layer and one output layer having tanh activation function. The output layer is used to flatten the matrix and convert it into 1D matrix. As, it was a huge image dataset, after deep study proceeded towards convolution neural network.

3.9 Convolution Neural Network

Initially, the dataset is uploaded and data cleaning is done by removing null values, replacing it by mean values, dropping insignificant columns, etc. Since, there are seven different classes to be classified of skin diseases, so it is multi class classification. The data is fed to the input layer, then it is passed through three hidden layers where complex computation is performed. The activation function used are Relu and then output is flattened i.e. converted to 1D and provided to the output. Since, the output is multi class classification, the activation function used is SoftMax activation function instead of sigmoid activation function. In hidden layers, two convolution 2D layer were provided with kernel size (3,3) and max pooling filter of 16*2 size. The optimizer used for the model is Adam. Then, the model is compiled and the learning set annealer is set. The data is then split into features and targets. Training and testing is performed on it. After defining the trained data and tested data, one hot encoding label is performed. There after the data augmentation is done to prevent overfitting. The batch size is 16. After the training, it is fitted to the model and various epochs were performed to enhance the accuracy and finally, the confusion matrix was plotted.

The image was also converted to grayscale and the gaussian filter was used to reduce the noise earlier and finally, the binary thresholding and Otsu thresholding was applied using ground tooth labels for the image. Thus, the predicted labels from the thresholded images were acquired.

4. RESULTS AND DISCUSSION

The results obtained below are through different image segmentation techniques. We processed each image of the Dataset and were able to get segmented images and classify the disease, but a major drawback of these segmentation techniques is the requirement of ground tooth masked images, obtaining these ground tooth masked images can be a very lengthy and time-consuming process and thus it led us to move towards different machine learning algorithms.

4.1 Segmentation techniques:

1. Basic Thresholding Output

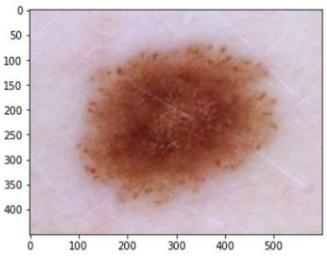

Fig 1: Original Image

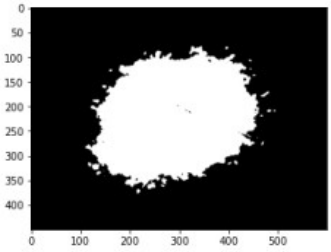

Fig 2: Detected area

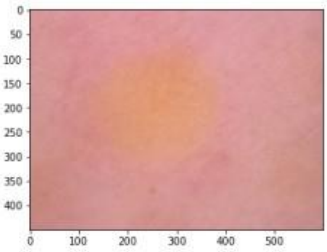

Fig 3: Original Image

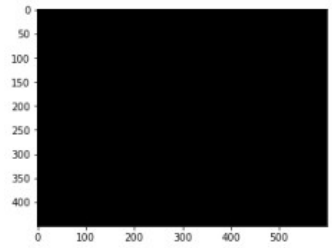

Fig 4: Disease not Detected

2. Entropy Based Thresholding

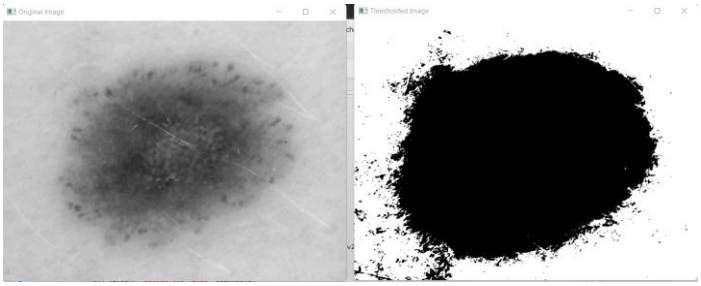

Fig 5: Original and Segmented Region

3. Boundary and spot detection

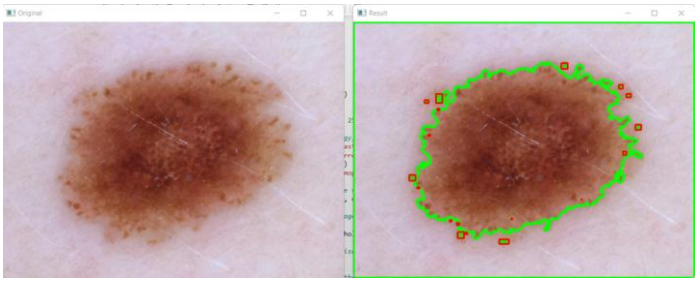

Fig 6: Boundary of the patch detected through Boundary Spot Detection

4. Otsu's Thresholding

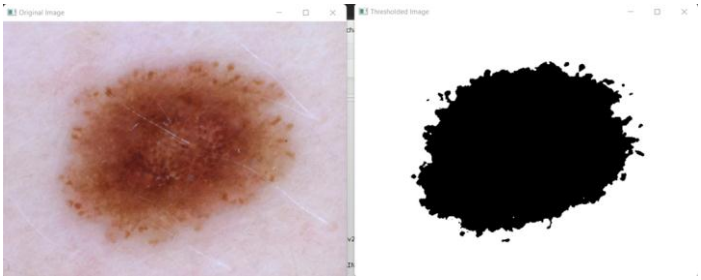

Fig 7: Patch detected through Otsu's Thresholding

a. Supervised Learning Algorithms

1. Decision Tree Classifier

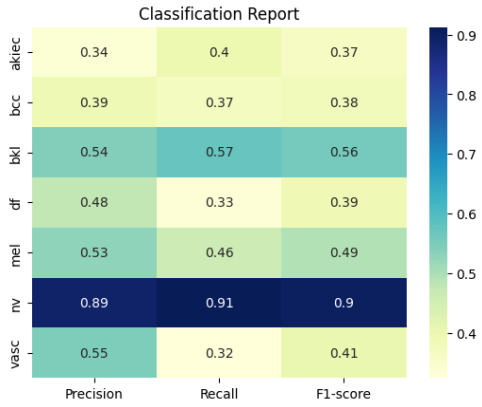

Fig 8

2. Support Vector Machine

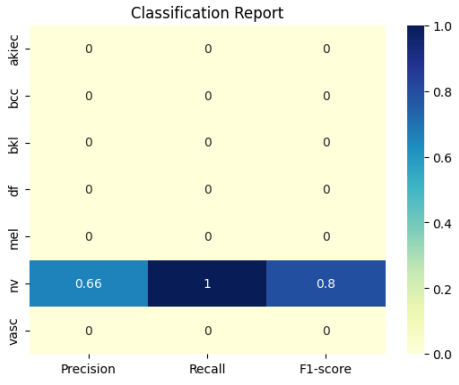

Fig 9

3. Random Forest Classifier

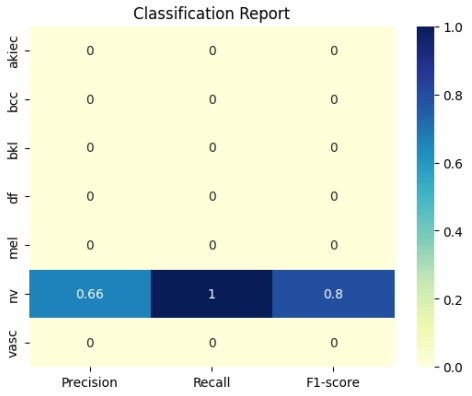

Fig 10

In Supervised Machine learning algorithms, we classified using Decision trees, Support Vector Machine, Random Forest and got maximum accuracies of 77.7%, 67%, 79.3% respectively. But due to low accuracies, overfitting and due to high biasness of the model led us to move further to deep learning.

b. Convolution Neural Network

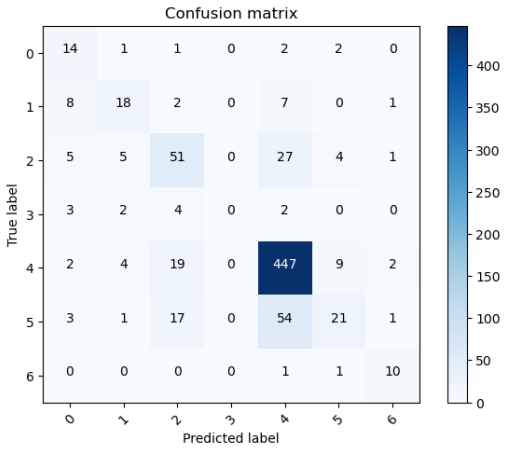

Fig 11

As per the studies, we found out that the Convolution Neural Network was the best suitable technique for the classification of diseases. Due to high computation capacity and the ability to classify a huge dataset, this model proved to be better than the other classification techniques that were used above. It also overcame the drawback of overfitting, and can classify new and unseen data while maintaining a high accuracy of 82%.

3. CONCLUSIONS

Using the HAM 10000 dataset, a comparison of multiple algorithms has been carried out in order to detect skin conditions and for the classification of skin conditions. When we began the research with fundamental image processing methods, we obtained the highest possible accuracy of 75%. However, when we moved on to classification algorithms, we obtained the highest possible accuracy of 97% in both the decision tree and the random forest. On the other hand, because of the problems associated with overfitting and the model becoming biased, we decided to move on to the neural network. Convolution neural network appears to be the most effective algorithm for the classification of images, according to our findings. We found that it was accurate 82% of the time, and it enabled us to verify that it worked appropriately with random data as well. Additionally, it assisted us in attaining a greater degree of precision.

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