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Skin detection and classification using run-length matrix and support vector machine

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Abstract— skin problems are a common cause of illness. The threats that infections offer to human health are not always obvious and can result in both physical and psychological distress. Moreover, under extreme conditions, skin cancer could be the outcome. The detection of skin illnesses from clinical pictures is thus one of the trickiest issues in medical field. Nevertheless,manual diagnosis of the lesion conditions by medical experts is subjective and takes a long time. In order to plan therapies more effectively, both doctors and patients need automatic lesion projection.Here , we present a solution for digital hair removal using MFs, such as the BlackHat transformation and the inpainting technique. The images are then subjected to Gaussian filtering to remove any blur or noise. Additionally, we automatically segment the impacted lesions using the Grabcut segmentation method. The feature extraction for lesion are discovered using Run Length Matrix (RLM) approaches. The skin images were correctly classified as Melanoma (MEL), Melanocytic nevus (NV), Basal cell carcinoma (BCC), Actinic keratosis (AK), Benign keratosis (BKL), Dermatofibroma (DF), Vascular lesion (VASC), and K-cell lymphoma using computationally efficient machine learning techniques—Support Vector Machine (SVM) (SCC). The models are often validated using two datasets: HAM10000 and ISIC 2019 Challenge. SVM performs marginally further on than alternative groups. A comparison between our work and cutting-edge approaches has also been made. Keywords— component, formatting, style, styling, insert (key words)

I. INTRODUCTION

There are many different organs in the human body. Skin is one of them. It spans the entire body and is the biggest organ in the human body. A dermatosis is any condition that affects the human skin.Skin disease is the most dangerous disease in the world.In 2018 almost 2,794 peoples died because of the skin cancer.This is a modification to your skin's texture. Dermatosis can be brought on by bacterial, fungal, allergy, or viral illnesses. Skin conditions are also influenced by genetics. Skin conditions typically affect the epidermis, the skin's thin outer layer that can be seen with the naked eye and can lead to bodily harm and psychological distress. The various types of skin lesions include actinic keratosis (AK), basal cell carcinoma (BCC), benign keratosis (BKL), dermatofibroma (DF), melanoma (MEL), melanocytic nevus (NV), squamous cell carcinoma (SCC), and vascular lesion (VASC). The symptoms and harshness of the lesions differ as well. fig.1. Some of them are either painful or not permanent, while others are only temporary. Melanoma is the deadliest and most serious form of these skin conditions. Until now, if skin conditions are caught early enough, about 95% of patients can be treated. The correct classification of skin disorders may benefit from automated computer systems. There will be significant knowledge space allying doctors and patients with leison illnesses because population are unaware of the types, symptoms, and stages of skin diseases. Sometimes symptoms don't show up for a while. This calls for quick and early detection. Yet, it can be challenging and expensive to accurately diagnose skin disorders in order to ascertain the kind and time of the disease. The different forms of skin conditions can now be identified more precisely and rapidly thanks to an automated computer system built on machine learning

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Fig.1. Skin disease image

2. Literature Review: Many studies have suggested different ways of classifying skin disorders.In this paper making different concept based on dataset,proposed methods,feature extraction and classification . This section looked through a number of important research articles to learn the methods and instruments used in previous research and to pinpoint any research gaps. Jagdish et al. [1] There have been numerous studies that have suggested various classifications for skin problems.Many classification algorithms are used like KNN and SVM.The K-Nearest Neighbor classification algorithm outperforms the Support Vector Machine (SVM) classification method with an accuracy of 91.2%,and the system used the classification method to identify skin disease types.However, they were limited to working with 50 sample photos with two classifications (basal and squamous disease). Naeem et al. [2] In this paper applied Support Vector Machine(SVM) and image processing techniques to see skin cancer.Different preprocessing procedures were used for noise removal and image enhancement, and several salient points were extracted from the images using the GLCM method. The classifier then decided whether the photos were hazardous or not. Bandyopadhyay et al. [3]Applying Machine Learning and Deep Learning to consolidate a model. For feature selection, they used deep neural networks for classification, they used SVM, DT, and ensemble boosting Adaboost classifiers. They conducted a comparison analysis to find the most effective prediction model. Kalaivani et al. [4 In addition to a proposed method that merges both data mining techniques into one group, a novel strategy that unites two distinct data mining methodologies has also been offered. Using the valuable skin specialist openly published dataset ISIC2019 image and the group of deep learning technique, they divided skin diseases into seven classes. They found that the ensemble method allowed them to more successfully and successfully than precisely see skin conditions. AlDera et al. [5]unveiled a psoriasis analyzer that can identify acne, cherry angioma, melanoma, and psoriasis from a snapshot of the affected skin. On the Dermnet NZ and Atlas Dermatologico databases, they used Otsu's method for picture segmentation, and the Gabor, Entropy, and

Sobel algorithms for feature extraction. They classified the data using the Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (K-NN) classifiers, with relative accuracy rates of 90.7%, 84.2%, and 67.1%. Kshirsagar et al. [6] Use of MobileNetV2 and LSTM to develop a classification system for skin diseases. They focused largely on the system's forecasting accuracy for skin diseases and made sure that Excel was effective at storing all relevant state data for precise projections. They also made comparisons with a number of other conventional models, including CNN and FTNN, and found that the suggested model performed better in both the classification of skin diseases and the evaluation of the development for cancer growth using texture-based data. Hatem et al. [7]Introduced the model as long as, recogonize leison diseases. Applied K closest neighbor (KNN) pointout to categorize skin diseases, only for the two classes did he reach an accuracy of 98%. Kethana et al.[8] suggested a convolutional neural network model for classifying skin disorders (CNN).From ISIC dataset is applied to prepare the dataset. Skin conditions such as melanoma, nevi, and seborrheic keratosis can be accurately identified 92% of the time. Padmavathi et al.[9] provided a deep learning network that has been trained and optimized for use in an automated system for classifying skin lesions. After assessing the performance using well known quantitative metrics including exactitude,vulnatability, preciseness and exactness, they evaluated the results using a variety of convey learning approaches. Maduranga et al [10] Introduced a mobile application for skin disease detection powered by artificial intelligence (AI). To categorize skin conditions, they used a convolutional neural network (CNN) on the HAM10000 dataset. Additionally, they used transfer learning and MobileNet to develop a mobile application for quick and precise matching that achieved 85% accuracy. Jaïn et al [11] suggested a brand-new best probabilistic deep neural network (OPDNN) for diagnosing skin conditions precisely. Prior to extracting features for optimum probabilistic deep neural network (OP-DNN) training, we first eliminated the images' extraneous information. We also reached 95% accuracy, 0.97 specificity, and 0.91 sensitivity using our optimization technique. Soliman [12] employing a Multiclass Support Vector Machine and a Convolutional Neural Network (CNN) that has been trained to extract relevant properties to identify skin disorders (SVM). As a result, the model was generally only able to classify three diseases: melanoma, eczema, and psoriasis. However, this work was limited to three diseases. As a result, This is does'nt follow a conventional pattern of other skin diseases. The research has a problem with this. Alquran et al. [13] The K-Nearest Neighbor grouping algorithm outperformed the Support Vector Machine (svm) grouping method with an excatness of 91.2, along with system used this classification method to identify skin disease types. Sintura et al.[14] presented a more comprehensive method for using image processing to identify skin problems. They split the diseased side initially using Otsu's method. Then, a few GLCM parameters, including area, perimeter, diameter, and entropy, were takeout. Gradually, they used SVM classification to divide the illnesses into four categories: melanoma, rosacea, psoriasis, and acne. The accuracy of this method in identifying skin issues is 89%. They only used a small number of features, and they only used this version on a small data construct table of 1000 images. This is a problem for the system. Kumar et al [15] developed a technique to identify the presence of melanoma in a given sample. The steps in this study included: gathering the labeled data from the preprocessed images, smoothing all the images, extracting the pixel intensities of the picture converted to a matrix, adding of these matrices to a database, using an appropriate kernel to obtain the labeled data, and finally adding all these matrices to the database. We successfully categorize patterns using the trained data after SVM training. Around 90% of the classifications are accurate. Sadly, they only discovered one illness. The system's primary drawback is this. Hamid et al.[16] suggested a sophisticated diagnostic system that scores various skin lesions. A deep convolutional neural network and an error-correcting output code (ECOC) support vector machine are used in combination to create the proposed methodology (SVM). The suggested method tries to grouping this lesion photos into different groups: benign or malignant melanoma, healthy, acne, eczema, and healthy. 9144 photos that were gathered from different sources and used in experiments. Using the pre-trained CNN model AlexNet, we extracted features. For catogorizing, the ECOC SVM classifier was applied. ECOC SVM produced an overall accuracy of 86.21%. Shanti et al.[17] suggested the method for detecting different kinds of eudermic sicknesses using laptop vision. The methodology technique includes a convolutional neural network which include approximately 11 layers: convolutional layers, activation layers, watershed layers, absolutely related layers, and soft-max classification. The structure is demonstrated using photos from the DermNet database. The database covers all kinds of skin situations, but makes a speciality of four foremost varieties of pores and skin situations: acne, keratosis, eczema herpeticum, and urticaria, every with 30 to 60 distinct trials. The accuracy of the proposed CNN classifier is 98.6% to 99.04%. but, they only done with some snap shots from 4 classes. this is the biggest disadvantage of this look at. Bhavani et al. [18] provided a technique for utilizing computer vision-based methods to identify various forms of dermatological skin problems. For feature extraction in the medical image, Inception v3, Mobilenet, and Resnet are three deep learning algorithms that are used. Medical image training and evaluation are done using the machine learning technique Logistic Regression. Combining three convolutional neural network architectures can result in significant efficiency. The approach might not be useful for multi-class classification because the project utilized in this work was numerically complicated ,in addition to data set only different types of eudermic illness. Hameed et al. [19] proposed a new Computer-aided Diagnosis (CAD) method for determining the causes of the most prevalent skin lesions (acne, eczema, psoriasis, benign and malignant melanoma). used the Otsu's thresholding approach, the Dull Razor method, and Gaussian filtering to extract the region of interest from which the features are extracted. A Support Vector Machine (SVM) with a quadratic kernel was applied to a number of retrieved color and texture features. 1800 photos were used in the experiment, and six classes were classified with 83% accuracy. However, the system was limited by the tiny size of the dataset. Hameed et al. [20] offered a technique that expanded on prior work and proposed a new classification scheme for multi-class classification. Throughout the experiments, about 1800 photos from six classes were used. The average accuracy of the quadratic SVM after 10-fold cross-validation was 94.74%. Ubale et al. [21] suggested a color part model for identifying , categorizing different lesion conditions. To extract features from photos, they employed the LAB color phase model and the HSV color phase model. Finally, they classified skin conditions (acne, papillomas, psoriasis, melanoma, mycosis, vitiligo, warts) using the K Nearest Neighbor (KNN) classification approach, which had 91.80% accuracy for the HSV color phase model and 81.60% accuracy for the color phase LAB Modelka. Sadly, the pre-processing is inadequate, and this study does not use a validated data set. Albawi et al. [22] Introduced distinct skin disease identification for melanoma, nevus, and atypical skin illnesses. To remove undesirable noisy areas from the input skin picture during the preprocessing stage, they used an adaptive filtering algorithm. The next step involved the efficient localization and region of interest (ROI) extraction of illness areas using an adaptive region growth technique. To extract pertinent characteristics, they employed a hybrid feature extraction technique that combined the two-dimension discrete wavelet transform (2D-DWT) with geometric and texture data. Eventually, the International Skin Imaging Collaboration (ISIC) dataset was subjected to convolutional neural networks (CNN) analysis. The disease classification accuracy for the suggested technique was 96.768%. Ozkan et al. [23] outlined the methodology for dividing eudermic lesions into many categories: melanoma, abnormal, and normal. They used the PH2 dataset to apply ANN, SVM, KNN, and DT, different ML techniques. For ANN, SVM, KNN, and DT, the model's accuracy was 92.50%, 89.50%, 82.00%, and 90.00%, respectively. Yet since there are only three classes in the dataset, the technique might not be effective for multiclass categorization. Above to be mentioned, This is concluded the majority of the work that came to be done thus far have been done so as to forecast depression in a certain group of people, such as patients with a particular ailment, people in a

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CERTAIN AGE RANGE, ETC. BY TAKING INTO ACCOUNT VARIOUS SOCIO-DEMOGRAPHIC DATA OF INDIVIDUALS WITH A RANGE OF AGES, HEALTH CONDITIONS,AND SOCIOECONOMIC POSITIONS, THIS STUDY ATTEMPTS TO GET OVER THIS LIMITATION.

3.PROPOSED METHODOLOGY

This section of the protocol describes and examines the suggested methods for classifying skin disorders. The following components make up the entire procedure. Fig. 2 contains the system's illustration.

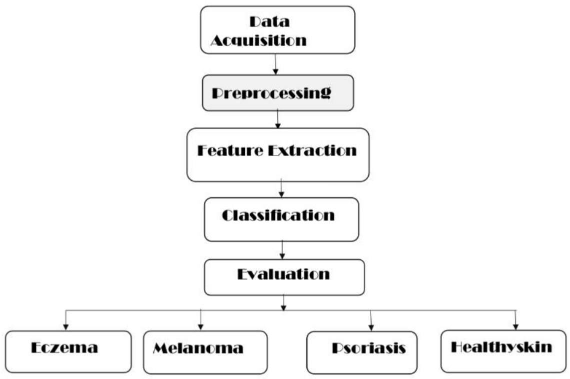
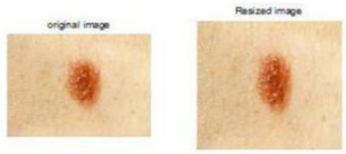


Fig.2.The proposed system block diagram

3.1 Data Acquisition: Data acquisition is the procedure of gathering information from numerous sources, such as sensors, devices, instruments, databases, or external systems, in order to be analyzed, processed, or stored. In the context of skin disease detection, data acquisition may involve collecting various types of data related to skin diseases, such as medical images, patient information, clinical data. Data acquisition can be performed manually, through direct measurements or observations, or automatically, using sensors or other devices that collect data continuously. The acquired data can then be processed and analyzed using various techniques such as machine learning, statistical analysis, or data visualization to extract meaningful insights or information. Units

3.2 Preprocessing: Before additional processing or analysis, a technique called "image preprocessing" is used to improve the quality of images. It involves a series of operations that are applied to the original image to improve its visual quality, reduce noise, and remove unwanted artifacts or distortions Image preprocessing's aim is to improve the precision and effectiveness of upcoming image analysis activities including segmentation, feature extraction, and classification.The flowchart are given below fig.3.

3.2.1 Image Resizing: The process of altering an image's proportions, either by enlarging or constricting it, is known as image resizing. This is done to adjust the scale or resolution of an image to suit a specific purpose, such as displaying it on a website, printing it on a document, or analyzing it in an image processing system. Fig.4 shows the original image and resized image.



(a) original image (b) Resized image

Fig.4. Original and Resized image

3.2.1 Color space conversion: Color space conversion, also called as color model conversion.It involves converting an image's colors from one color space to another.It is mathematical to express colours is a space of the spectrum of colors that can be seen on a screen or printed. Digital images use different color spaces, including RGB (red, green, blue), CMYK (cyan, magenta, yellow, black), HSL (Hue Saturated Lightness), and HSV (Hue Saturation Value). Fig.5 displays both the original image and the converted color space.

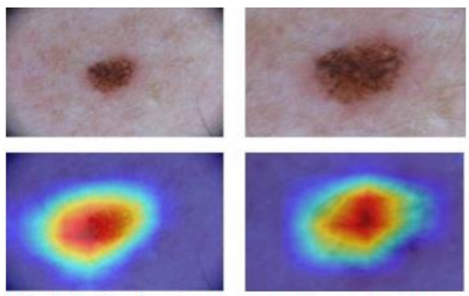


Fig.5. Original and color space Conversion image

3.2.2 Contrast Enhancement: We look at the issues that arise frequently when analyzing dermoscopy images, such as inadequate contrast and improper color calibration. Varying lighting or different imaging technologies will provide varied picture colors and hence, different colors of the same lesion will cause problems during the segmentation stage. In a similar vein, low contrast makes precise border recognition challenging . Hence, as a preprocessing step, we adopt an automated color equalization technique (ACE) to address these difficulties.”.

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3.3 Feature Extraction: For researching and figuring out the underlying connections between various things, feature extraction is crucial. The categorization, prediction, and recommendation algorithms for photos are not capable of understanding images instantly. In order to convert them into forms that may be utilised, feature extraction is necessary. The dermoscopic image can be described by a variety of factors. Regrettably, not all traits can be utilized to classify skin issues. As a result, classification accuracy decreases as the classifier grows more complicated and expends more processing resources on a number of irrelevant characteristics. The best qualities in photographs of skin cancer must correspond to the local characteristics. As a result, it is necessary to recover enough features to identify images as precisely as is practical.

3.3.1.Run Length Matrix: A 2D matrix called the run length matrix has an element P(i, j) that contains the number of pixels where the gray level I has length j depending on the direction. The greatest gray level is represented by the first dimension of the 2D matrix, while the longest waveform is represented by the second dimension. For texture analysis, it is possible to extract texture features using a gray level run-length matrix (GLRLM). Higher-order statistical texture features can be acquired using the GLRLM approach. A group of pixels that all have the same intensity value and are oriented in the same direction make up a gray level. The distribution and connectivity of image pixels are statistically captured in a gray level run length matrix (GRLLM), which is a common technique for gathering data from medical pictures like magnetic resonance (MR) imaging. Equations are shown in Table 1.

	$N_z(\theta)$
Long Run Emphasis	$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r} P(i,j\|\theta)\, j^2}{N_{z(\theta)}}$
Gray Level Non-uniformity	$\frac{\sum_{i=1}^{N_g}(\sum_{j=1}^{N_r} P(i,j\|\theta))^2}{N_z(\theta)}$
Run length nonuniformity	$\frac{\sum_{j=1}^{N_r}\left(\sum_{i=1}^{N_g} P(i,j\|\theta)\right)^2}{N_z(\theta)}$
Run percentage	$\frac{N_{z(\theta)}}{N_p}$
Low Gray level Run Emphasis	$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\frac{P(i,j\|\theta)}{j^2}}{N_z(\theta)}$

Table.1

(i) Dimension has a length equal to the maximum gray level (bin values) and corresponds to the gray level.
(j) Dimension matches the run length (bin values) and has a length equal to the longest possible run length

3.4.Classification: The process of breaking up a vast amount of data into various groups. In the study, types of epidermis illnesses were predicted using characteristics gleaned from photo data. Depending on the application and the kind of data collection, many classification approaches are employed. We chose supervised classification methods like support vector machines for this investigation (SVM). Using a multiclass SVM that incorporates the One-to-One and One-to-Rest techniques, eight skin conditions were categorized [24]. It converts data using a kernel technique and chooses, from a range of options, the optimum decision boundary. [25]

Dataset Preparation

"Basal cell cancer (BCC), actinic keratosis (AK), melanoma (MEL), melanocytic nevus (NV), benign keratosis (BKL), and dermatofibroma" are the 8 categories in the ISIC 2019 test training dataset (DF).It is composed of 25331 pictures from vascular lesions (VASC) and squamous cells (SCC). DF Class 239 Photos, AK Class 867 Pictures, BCC Class 3323 Photographs, BKL Class 2624 Images, MEL Class 4522 Images, Class 12875 Images, and SCC 628 class pictures and 253 VASC class images make up the one unbalanced dataset. The HAM10000 dataset likewise has an imbalanced number of photos, with 327 images belonging to the AK class, 514 to the BCC class, 1099 to the BKL class, 115 to the DF class, 1113 to the MEL class, and 6705 to the VASC class. VASC classes are depicted in 142 photos. The ISIC 2019 dataset's data distribution for each class is as follows: There is a propensity to overestimate the majority class and frequently disregard the minority class when training models using unbalanced datasets. Errors in the minority class thus rise, whereas errors in the majority class fall. Unbalanced data sets for both data sets were addressed using a data balancing random oversampling method.fig.7 shown the dataset of eight skin diseases.

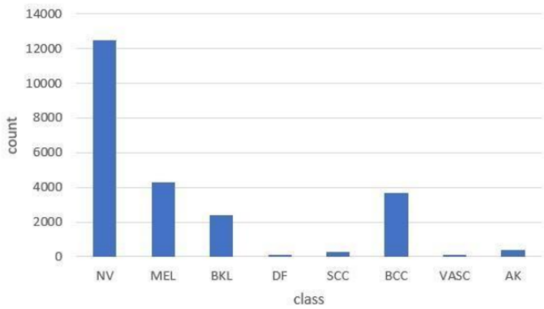

Fig.7. The division of the entire collection of images into eight classes

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4.RESULT AND DISCUSSION

SVM is a statistical technique for classifying small sample sizes that is based on statistical theory. By predicting the test set from the given training set, it may determine the least training error and a confidence interval term. In this study, SVM is utilized to differentiate between three different skin conditions. The obtained classification (such as color and texture data) are apply to select sample size and training size before the support vector machine's rational kernel function is used to build the classification model. Eight common skin problems Benign keratosis (BKL), Actinic keratosis (AK), Basal Cell Carcinoma (BCC), melanoma (MEL), melanocytic nevus (NV), squamous cell carcinoma (SCC), and Vascular Lesion (VASC) .The lesion area feature classifier employs SVM1, the integrated classifier employs SVM2, and the texture feature classifier employs SVM1. We modify the different penalty components according to this framework in order to classify the maize diseases. fx=sgn∑j=1najyjkxi, xj+b ,kxi, xj=exp−xi−xj22σ2

A radial basis function parameter value, xi denotes the eigenvector generated by the characteristic model, and yj denotes the outcomes. Where k(xi, xj) is a kernel function,b* is the bias, and aj is a Lagrange multiplier.

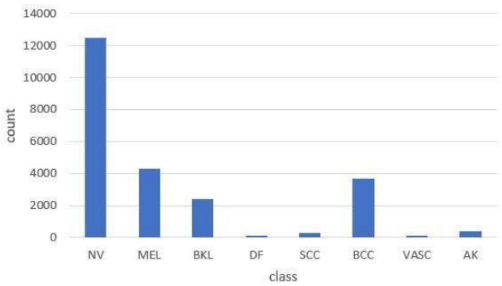

Fig.7. The division of the entire collection of images into eight classes

Table 2 displays the outcomes of various recognition techniques. Different types of test samples and standard samples of each skin illness are used to identify the images on them. The accuracy is just 20%, 15%, 75%, 20%, 16%, 80%, 20%, 16%, 80% for eight diseases. The one-way detection of textural characteristics method used by De et al. [26] is prone to fairly large mistakes. In contrast, the identification accuracy rate in a study by De et al. [26] was 20%, 15%, 75%, 20%, 16%, and 80%, and the support vector machine and genetic algorithm approach were utilized with incredibly high efficacy. In this study, it is demonstrated that color and texture cues can be employed to make up for one-way recognition's drawbacks, boosting both the recognition rate and accuracy to 90% and higher. Vertical image segmentation, which may generate ten local vertical pictures after segmentation, can improve the accuracy of skin disease detection

Conclusion

Currently, skin illness is an issue on a global scale. Many sorts of skin diseases affect people from many different nations or areas. By creating new methods and procedures, we can combat these diseases. We have worked with numerous phases in this study project. We employed automatic Grabcut segmentation to precisely segment and find the illness area in order to identify the skin lesion. Lastly, we classified the type of skin disease using SVM classifiers after extracting RLM and statistical information. ISIC 2019 Challenge and HAM10000 were two publicly accessible benchmark datasets that we used. We employed an automatic segmentation approach, which occasionally fails to recognize the skin lesion. As a result, misclassification results, which is a shortcoming of our work. Future work will concentrate on improving segmentation and classification methods, such as ensemble learning and deep learning, for real-time skin disease detection. Additionally, we think it will improve the efficiency and precision of object detection and image categorization methods. In order to maintain healthy skin, we expect that early illness detection will be helpful for patients

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