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A Novel Technique for Skin Disease Detection Using Machine-Learning Techniques



ABSTRACT

Worldwide, skin issues are frequent. Health problems and depression may result from obscured infections. Severe mutations may cause skin cancer. Therefore, investigating and detecting skin lesions from real time clinical images is one of the toughest medical image-processing challenges. Physically diagnosing skin issues takes time and is unreliable for dermatologists. Thus, patients and doctors need computerized inflammation prediction to programme treatments quickly. This work uses morphological filtering like Black-Hat transformation and inpainting for digital hair removal and Gaussian filtering for image deblurring. We identify troublesome skin lesions using automatic Grabcut segmentation. We determine skin image input patterns using GLCM and analytical characteristics. Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) classifiers distinguish skin images as melanoma (MEL), melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis (AK), BKL, Squamous cell carcinoma (SCC), Eczema (EZ) and Psoriasis (PS) using features extracted. SVM outperforms the other two classifiers. The SIIM-ISIC 2020 challenge, Dermnet and HAM10000 verified the models. Our work was also compared to the contemporary state-of-art approaches.

Keywords: Skin lesion, Machine Learning, Support Vector Machine, K Nearest Neighbor (KNN), Eczema, Psoriasis.

1. INTRODUCTION

Humans have several organs. Skin is one. It is the body's largest organ [1]. A skin disorder is defined as a problem with the skin [2]. Infections of the skin are among the most contagious. As of 2018, 27,94 skin cancer-related fatalities were recorded in Bangladesh, according to the World Health Organization [3]. In 2018, the World Health Organization recorded more than 14 million illnesses, with 9.6 million deaths [4]. Allergies, fungi, viruses, and bacteria are the main causes of skin problems [5]. Some skin disorders have a hereditary component. Experiencing visible skin illnesses may lead to mental distress and discomfort for individuals.

Lesions may range in severity type and severity, as seen in Figure 1, and can include actinic keratosis (AK), basal cell carcinoma (BCC), benign keratosis (BKL), melanoma (MEL), melanocytic nevus (NV), squamous cell carcinoma (SCC), Eczema (EZ) and Psoriasis (PS). They might be chronic or transient and severe or mild. Melanoma is the deadliest skin disorder. If diagnosed early, 95% of skin condition patients get better. Skin diagnosis and treatment may be improved using automated technology. Many individuals are unaware of skin disorder classifications, signs, and phases; therefore, dermatologists and patients are confined. The indications may take a while to appear. This necessitates initial and prompt identification. Accurately diagnosing skin problems to establish their type and phase may be a complex and expensive process. The autonomous computerized approach based on machine learning can diagnose skin disorders faster and more precisely. Many researchers have classified skin diseases for 30 years. The area is an important and popular study issue. Despite numerous skin diseases being identified and categorization studies, an issue remains. Many approaches fail to categorize several types [8]. Multiple class categorization is difficult since skin diseases behave similarly.

Description of this research's primary contribution:

- Create a Black-Hat Transformation and Image Inpainting hair removal technique.
- To create a strong Grabcut image segmentation model that identifies the lesion without losing details and improves image processing.
- Build an automated skin disorder classification model with high accuracy using enough appropriate characteristics.

Section 2 covers the relevant literature review and the related issues. The suggested technique includes preprocessing, skin lesion categorization, extraction of features, and skin disorder classification in section 3. The recommended datasets and data preprocessing approaches are covered in section 4. Section 5 details the experimental findings of the proposed method. The remainder of this section discusses performance assessment and statistical analysis. The analysis finishes with future possibilities in section 6.

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2. LITERATURE REVIEW

Various approaches for classifying skin disorders have been proposed by researchers. Study types include datasets, feature extraction, selection, and classification models. We analyzed relevant research articles to look at previous methods and find gaps in the literature. A model for image processing that may identify skin diseases was suggested by Jagdish et al. [9]. Fifteen sample images were subjected to wavelet analysis, kernel neural network (KNN), support vector machine (SVM) classification, and fuzzy clustering. With a 91.2% accuracy rate, the K-nearest neighbor classification outperformed the Support Vector Machine. Just fifty photos from two categories of pathology (basal and squamous) were reviewed. Image processing and Support Vector Machines were used to predict skin cancer by Naeem et al. [10]. Pre-processing methods were used to reduce the noise and enhance the image quality, while GLCM extracts the features from images. The algorithm then identifies images as cancerous or normal. Using a hybrid approach, Bandyopadhyay et al. [11] integrated deep learning with machine learning. The feature extraction and classification processes make use of the following models: Alexnet, Googlenet, Resnet50, and VGG16. The following classifiers were used: Adaboost Ensemble Boosting, Decision Tree, and Support Vector Machine. The optimal prediction model was identified by an evaluation. Two data mining techniques were combined into a collaborative approach and strategy by Kalaivani et al. [12]. We observed that this method was more accurate for skin issue diagnosis when we utilized the relevant Dermatology ISIC2019 image dataset to categorize skin problems into seven categories utilizing cooperative deep learning methods. A skin problem diagnosis paradigm for psoriasis, lymphoma, hemangiomas, and acne was created by AlDera et al. [13]. Otsu's method split up images, and features were retrieved from the dermnet NZ and atlas dermatological by Gabor, Entropy, and Sobel. Classification accuracy was 90.7% with SVM, 84.2% with RF, and 67.1% with K-NN. Using MobileNetV2 and LSTM, Kshirsagar et al. [14] suggested a technique for classifying skin disorders.

To achieve this goal, we optimized the storage of full-state details for accurate predictions and made sure that skin disorder predictions were as precise as possible. When it came to skin disease classification and tracking tumor progression using texture-based data, their model beat CNN and FTNN. Hatem [15] designed a system for detecting skin lesions and classifying them as benign or normal, which achieved an accuracy of 98% with the K nearest neighbour (KNN) classifier. Using 10015 images from the ISIC 2020 dataset, Kethana et al. [16] trained a Convolutional Neural Network (CNN) model to classify skin disorders, including melanoma, nevus, and seborrheic keratosis, with a 92% accuracy rate. Yao et al. [17] proposed a single-model approach for classifying skin lesions on small and imbalanced datasets. They initially trained various Deep Convolutional Neural Network (DCNN) on these datasets, then added regularization DropOut and DropBlock to restrict overfitting, and the Modified RandAugment augmentation system to deal with the deficiency of undersampling in small datasets. To counter the issue of unequal sample size and classification difficulty, the novel Multi-Weighted New Loss (MWNL) function and the end-to-end cumulative learning strategy (CLS) were used. This model achieved high classification performance while using minimal computational resources and inference time. Padmavathi et al. [18] used a preconditioned and customized deep learning system to classify skin lesions automatically. They evaluated several transfer learning approaches using metrics which include specificity, sensitivity, precision, and accuracy. Maduranga et al. [19] developed a deep learning-based smartphone app to identify skin problems using CNNs using the HAM10000 dataset. They generated an 85% accurate smartphone app adopting MobileNet and transfer learning. Jain et al. [20] suggested an optimum probability-based deep neural network (OP-DNN) for dermatological diagnosis. The images were processed to eliminate unnecessary components, then features were retrieved for OP-DNN training. A refinement strategy yielded 95% accuracy, 0.97 specificity, and 0.91 sensitivity. Soliman [5] classified skin disorders using a multiclass SVM and a pre-trained CNN. To classify melanoma, eczema, and psoriasis, the model averaged 100% accuracy. However, the research only examined three disorders, making it an inadequate model for other skin conditions.

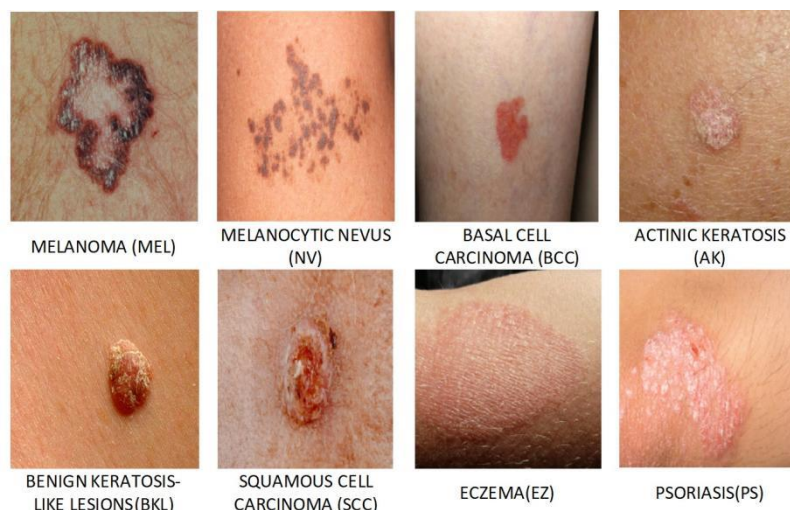


Figure 1. Sample of Skin lesion Images collected from the Dermnet, ISIC 2020 and HAM10000 Dataset

Using dermoscopy images GLCM, appearance, and wavelet features, Janney et al. [21] implemented SVM, ANN, and Naive Bayes Classifier. The accuracy rates of ANN, SVM, and Naive Bayes classifiers were 89%, 71%, and 71%, respectively, while evaluating classification methodologies. Its SVM and Naive Bayes Classifier performed poorly, which is a major drawback. Using a support vector machine (SVM) classifier, Alquran et al. [22] were able to categorize skin images as either healthy or diseased. To identify skin image features, the GLCM and ABCD metrics were used. Principal Component Analysis (PCA) was then used to determine the most relevant characteristics. The method's average accuracy was 92.1%, which is inadequate for more than two classes. Using the Naive Bayes classifier to classify diseases and the dynamic graph cut approach to segment lesions, Balaji et al. [23] created a system for skin condition detection and classification. The resulting method outperformed FCN and SegNet in terms of illness classification on the ISIC 2017 dataset by 6.5 and 8.7 percentage points, respectively. Image processing was used by Sinthura et al. [24] to enhance skin disorder detection. At first, we used Otsu's method to segregate the disease then they retrieved GLCM properties including area, perimeter, mean, and entropy. In the end, they used the SVM classifier to detect rosacea, acne, psoriasis, and melanoma. This approach was 89% accurate. The minimal dataset of 100 photos and few attributes hampered it. Kumar et al. [25] suggested a melanoma detection technique. The research collected labeled data from preprocessed images, flattened them, and extracted the pixel intensities into an array. It then appended all collected arrays to a database, trained the SVM with an appropriate kernel, and classified the samples according to their intensity. About 90% of classifications were correct. The biggest shortcoming of the approach was that it focuses on only one disorder. Hameed et al. [26] created an automated multiclass skin lesion categorization algorithm. This method used a deep convolutional neural network with an EOC SVM. It classifies skin images as healthy, acne, eczema, mild, or malignant melanoma. Pre-trained CNN model AlexNet was used for feature extraction and tested 9,144 images which were collected from different sources. Classification using ECOC SVM classifier with 86.21% accuracy.

3. PROPOSED METHODOLOGY

This part covers skin disorder classification methods. The four phases are preprocessing, segmentation, feature extraction, and classification (Figure. 2). Images are preprocessed to lend them better usable. Hair, noise, and deformation in skin images may slow down image processing. Preprocessing improves picture quality, reduces complications, and increases accuracy. Image scaling to 512×512 , hair removal, and noise reduction are included. This reduces processing duration and ensures that images of different resolutions have similar properties. Images acquired for skin disorders should ideally not include any hairs. Common methods for hair removal include the median filter[34], adaptive threshold[35], Gabor filtering, PDE-based inpainting[36], and the Top Hat filter [37,38]. We advise using digital hair removal (DHR) methods, such as inpainting and Black-Hat transformation algorithms, to get rid of unwanted hair.

A brief outline of the DHR method:

1. Making grayscale images from RGB ones
2. Modifying structural black-and-white images
3. Create an inpainting mask
4. Applying the inpainting technique to an initial image employing the mask

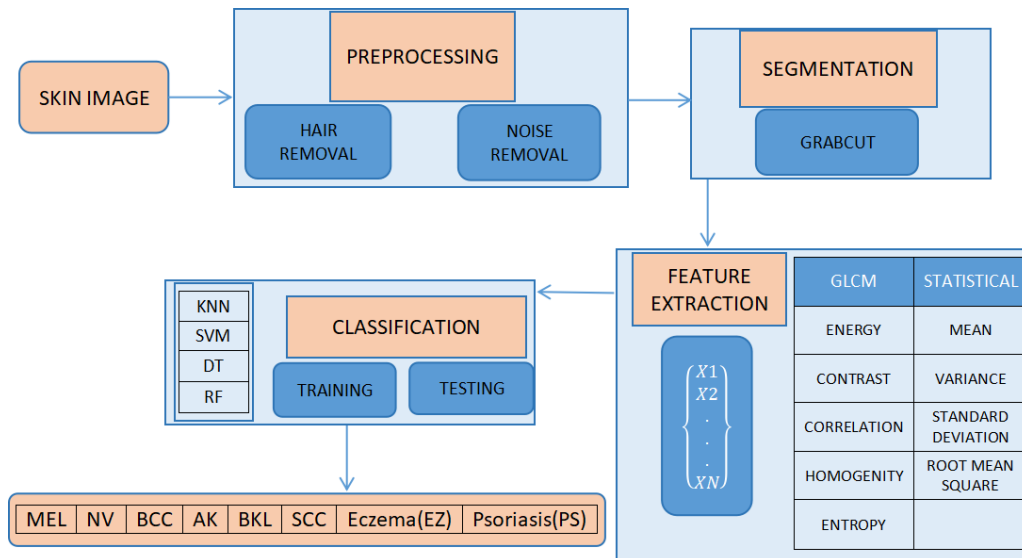


Figure 2. A Detailed Block Diagram of Novel Skin Diseases Detection System.

Extracting, transmitting, and processing digital images having noise. Excessive hue and luminance fluctuations degrade the picture quality. Image blurring and noise reduction techniques include median, mean, and bilateral filtering [39]. This technique uses Gaussian filtering to blur and eliminate noise. This approach employs kernel augmentation. Using features such as appearance, grayscale, saturation, contrast, etc., image segmentation may split an image into non-

overlapping sections. Segmenting images properly helps to analyze them and distinguish healthy from diseased skin. The significant variances in color, size, and form of lesions make segmenting microscopic images challenging. Image segmentation methods include threshold-based, region-based, cluster-based, and edge-based [40-43]. This study segments images using the Grabcut method and estimates the target item and background color dissemination using a Gaussian Mixture Model. This approach dynamically constructs a rectangle and isolates the emphasized features from background images with little user involvement. Feature extraction helps analyze and comprehend various object relationships. Estimation, suggestions, and classification techniques are unable to comprehend images.

To make them usable, feature extraction is essential. The skin images are described by several characteristics; however, not all these characteristics are required for classifying skin disorders which makes the classifier more complicated, computationally expensive, and decreases classification accuracy. The best features to use with skin lesion images should detail the local traits. Thus, ample characteristics must be retrieved for utmost accuracy. Segmented region of interest images are ideal for separately processing the area since they pull out different characteristics. This study identified skin diseases using GLCM texture and color scene statistical characteristics. To begin, we use the Gray Level Co-occurrence Matrix to work out every image. The following are calculated from the matrix: entropy, coherence, energy, uniformity and contrast. The calculations, descriptions, and properties of the Gray Level C-Matrix are shown in Table 1. Data analysis was performed by looking at the RGB hues of considered image. As analytical features, it obtained RMS, variance, SD, and mean. Table 2 lists collected characteristics, descriptions, and formulas used. Table 3 displays determined parameters from imported images.

Table 1. List of Different GLCM features

List of Features	Formula	Description
Energy	$E = \sum_{i,j=0}^{N-1} (P_{ij})^2$	Defined as the sum of squared elements in GLCM with a value from 0 to 1.
Contrast	$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}(i - j)^2$	It is the overall intensity of the pixel with its neighbors
Correlation	$\text{Corr} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i - \mu)(j - \mu)}{\sigma^2}$	It returns a measure of how closely a pixel is connected to its neighbors in the entire image. μ is the mean and σ is the variance.
Homogeneity	$H = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1 + (i - j)^2}$	Closeness rate of distributed elements in GLCM
Entropy	$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij}$	Degree of Uniformity between pixels within the image and randomness

Table 2. List of Statistical features

List of Features	Formula	Description
Mean	$\text{Mean} = \sum_{i,j=0}^{N-1} iP_{ij}$	Average color value in the image
Variance	$\text{Variance} = \sum_{i,j=0}^{N-1} P_{ij}(i - \mu)^2$	Measure of the dispersion of the values around the mean
Standard Deviation	$\text{SD} = \sqrt{\sum_{i,j=0}^{N-1} P_{ij}(i - \mu)^2}$	Square root of variance
RMS	$\text{RMS} = \sqrt{\sum_{i,j=0}^{N-1} P_{ij}(i - C)^2}$	Square root of the average of all squared intensity values. C is the correlation constant

Table 3. Computational features Obtained

Image	Energy	Correlation	Contrast	Homogeneity	Entropy	Mean	Variance	SD	RMS
ISIC_0000000	0.44	0.99	0.1107	0.9978	3.5456	103.8	8976.2	102.7	11.08
ISIC_0000001	0.83	0.98	0.0245	0.9878	1.3455	7.849	616.09	27.45	2.89
ISIC_0000002	0.28	0.96	0.2755	0.9778	6.5678	133.9	4122.9	73.109	13.8
ISIC_0000003	0.24	0.98	0.0238	0.9908	5.9987	31.93	4567.9	83.001	10.89
ISIC_0000004	0.64	0.99	0.1933	0.9878	1.3944	8.09	5465.8	21.098	6.033
ISIC_0000005	0.87	0.97	0.1109	0.9968	2.9064	12.90	1624.4	59.77	2.89
RE00000001	0.82	0.95	0.0688	0.9778	1.9344	26.67	861.0	48.5	13.6
RE00000002	0.79	0.96	0.2333	0.9888	2.8035	9.70	1781.6	32.7	6.18

Image categorization is the final stage. Data is sorted into distinguished classes. This model detects skin disorders using image attributes. Classification using SVM, KNN, and DT. The supervised classification method SVM addresses classification and regression challenges. It achieves more accuracy than most algorithms. To categorize eight skin illnesses, we used an dual SVM with two systems, One-to-One and One-to-Rest [44].

This study transforms data using the kernel approach to get the best output determination threshold [45]. K-nearest neighbor (KNN) is an empirical classification and regression method. Undefined data points are valued by comparing 'feature similarity' to previous examples. This study calculates the Euclidean distance between new and existing examples to identify their similarities [46]. We utilized k=10 neighbors for better categorization. The decision tree represents knowledge as a tree of distinct regulations. It rapidly classifies unfamiliar records, which is helpful. We picked the classifier as it supports numerous variants of features and decision criteria across all categorization phases.

4. DATASET

The study we conducted employed the "International Skin Imaging Collaboration (ISIC) 2020" test dataset, Dermnet and the "HAM10000 (Human-Against-Machine with 10000 training images)" dataset. Our model was trained, tested, and evaluated using these datasets.

ISIC 2020 Challenge Dataset:

ISIC is an international database of dermoscopy images used in both the science and medicine fields [47]. We utilized just the ISIC 2020 training dataset, which has 31126 photos divided into eight categories: "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)".

Dermnet Dataset:

The total number of images are around 19,500, out of which approximately 15,500 have been split in the training set and the remaining in the test set. Eczema (EZ) and Psoriasis (PS) lesions are covered.

HAM10000 Dataset

Among the 10015 skin images included in the HAM10000 datasets from patients in Australia and Austria. Centrally cropped, every image has dimensions of 600 × 450. Actinic keratosis (AK), basal cell carcinoma (BCC), benign keratosis (BKL), dermatofibroma (DF), melanoma (MEL), melanocytic nevus (NV), and vascular lesion (VASC) are the seven types of lesions covered in the dataset.

5. RESULTS AND DISCUSSION

To prove the suggested approaches excellence, we performed all tasks on the Python platform and deployed the generated model to the ISIC 2020 challenge training dataset with 31126 photos of eight classes, Dermnet with 1800 photos of two classes and the HAM10000 dataset. During image preprocessing resizing the input image to 512 × 512 decreases execution time and enhances the performance of the model. We eliminate hairs using the Digital Hair Removal (DHR) method, which uses morphological filtering such as black transformation and picture inpainting. Using Gaussian filtering with a 7x7 kernel and sigma value noise from input images was eliminated. After automated Hair Removal and Gaussian filtering, we measure RMSE, PSNR, SSIM, SAM, and UIQ for the images, as shown in Tables 4 and 5. To locate the main feature of skin disorders we use the k-means and Automatic Grabcut segmentation algorithms in the preprocessing phase. The Grabcut technique is more effective in identifying skin lesions. To remove residual noise, we use Gaussian filtering. To categorize skin conditions, we extracted GLCM and analytical characteristics from categorized images and constructed a feature vector. We added SVM, KNN, RF and DT algorithms. We built the model using 80% of skin image data for training and tested on 20% of the testing data set. The suggested classification methods were further tested on the SIIM-ISIC 2020 challenge dataset, Dermnet and HAM10000 dataset.

Table 3. Statistical values after applying Digital-HR Technique

Image	PSNR	SSIM	RMSE	SAM	UIQ
ISIC_0000511	20.25	0.90	24.9	0.12	0.91
ISIC_0000562	26.90	0.89	10.45	0.06	0.92
RE000001002	22.80	0.91	13.90	0.10	0.91
RE000001003	27.53	0.88	13.7	0.06	0.93
RE000001004	24.35	0.86	21.5	0.12	0.90

Table 3. Statistical values after applying Gaussian Technique

Image	PSNR	SSIM	RMSE	SAM	UIQ
ISIC_0000000	39.05	0.72	2.98	0.05	0.93
ISIC_0000001	36.75	0.87	3.09	0.04	0.92
RE000001005	42.32	0.63	3.12	0.02	0.92
RE000001006	38.65	0.81	3.54	0.03	0.93
RE000001007	38.12	0.73	3.90	0.04	0.92

6. CONCLUSION AND FUTURE WORK

Skin lesions are universal. Different skin disorders burden peoples worldwide. Different technological ways and tactics may help us fight them. The research was done in phases. Applying a Gaussian Filter to blur images and Morphological Black-Hat Transformation for automated hair removal. After that, the skin lesion was discovered and the disease area was established using an automatic Grabcut segmentation. The last step was to include GLC-Matrix and a handful of analytical features into SVM, KNN, RF and DT classifiers so that they could identify skin disorders. The ISIC 2020 challenge, Dermnet and HAM10000 freely accessible public datasets, were used.

Due to the inappropriateness of these datasets, random oversampling was used to achieve analytical equivalence. The ISIC 2020 dataset achieved an average accuracy of 91% with SVM, 93% with KNN, 92% with RF and 91.5% with DT classifiers. Regarding the HAM10000 dataset, SVM, KNN, RF and DT classifiers achieved 90%, 91%, 91.4% and 93% accuracy, respectively. Accordingly, ISIC2020 was a more effective predictor of model performance than HAM10000. Our model performed well with balanced data. Our skin disorder categorization model outperformed certain leading approaches. However, classification performance may be improved. Our work is limited by the automated segmentation technique, which sometimes misclassifies skin lesions. We expect future research to concentrate on real-time skin disease detection and analysis of Eczema and psoriasis using ensemble learning and deep learning for segmentation and classification. Additionally, we believe it will improve image categorization and object identification techniques. We consider this will help people spot disorders early detection and preserve skin health.

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