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Psoriasis Skin Disease Classification based on Clinical Images

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Abstract: Psoriasis is an autoimmune skin disorder that causes skin plaques to develop into red and scaly patches. It affects millions of people globally. Dermatologists currently employ visual and haptic methods to determine a medical issue's severity. Intelligent medical imaging-based diagnosis systems are now a possibility because of the relatively recent development of deep learning technologies for medical image processing. These systems can help a human expert make better decisions about a patient's health. Convolutional neural networks, or CNNs, on the other hand, have achieved imaging performance levels comparable to, if not better than, those of humans. In the paper, a Dermnet dataset is used. Image preprocessing, fuzzy c-mean-based segmentation, MobileNet-based feature extraction, and a support vector machine (SVM) classification are used for skin disease classification. Dermnet's dataset was investigated for images of skin conditions using three classes Psoriasis, Dermatofibroma, and Melanoma are studied. The performance metrics such as accuracy, precision-recall, and f1-score are evaluated and compared for three classes of skin diseases. Despite working with a smaller dataset, MobileNet with Support Vector Machine outperforms ResNet in terms of accuracy (99.12%), precision (98.65%), and recall (99.66%).

Keywords- Dermatology, Psoriasis, Classification. SVM, MobileNet.

I. INTRODUCTION

An experienced specialist gathers and analyses data on skin quality features regularly. This expert employs a grading system that assigns an agreed-upon quality grade to unusual skin samples, either live or from images. On the other hand, utilizing machine vision to determine skin characteristics is advantageous since it gives an objective inspection [1, 2]. Because a professional's competence and expertise are subjective and may vary depending on who is grading, this helps avoid issues with repeatability and reproducibility. This may result in reduced expenses, more efficient analysis, and an accurate assessment of the patient's skin quality [3]. To create effective pharmacological treatment quickly, the dermatologist's visual assessments of the patient's skin must have an independent. Over the past few years, various skin inspection methods have been developed. These techniques include, for example, an evaluation of the skin's appearance around the pores on the face [4], an assessment of facial wrinkle improvements as time passes [5,] and an assessment of facial wrinkles using quantification methods and automatic detection [6]. More than half of these reviews were subjective, concentrating on the clinical perspective and professional judgment rather than a neutral assessment. Lichen planus papules and plaques have a pruritic, polygonal, violaceous, and flat-topped, irritating appearance as shown in Figure 1. Given that it can affect people of any age, most believe it is a disease that only affects adults. This lichen has multiple varieties, including annulus lichen planus, also known as atrophic lichen planus, inverse lichen planus, and longitudinal lichen planus. Dermatologists pay particular attention to the four P's during a clinical examination: purple, polygonal, irritable, and flat-topped papules. They also look for distinguishing characteristics such as a red or violet coloration and the Koebner phenomenon. During the histological diagnosis phase, light microscopic examination of lichen planus lesions reveals severe, shaped-like wedges hypergranulosis in the outermost layer of skin that is the epidermis, significant hyperkeratosis, and irregular sawtooth-like acanthosis of rete ridges. All of the features mentioned above are associated with the disease lichen planus. The upper dermis often consists of a thick, band-like lymphocytic infiltrate that can conceal the dermal-epidermal interface rather than a densely packed band-like lymphocytic infiltrate that may conceal the dermal-epidermal interface. This is due to keratinocytes undergoing apoptosis in the upper dermis.

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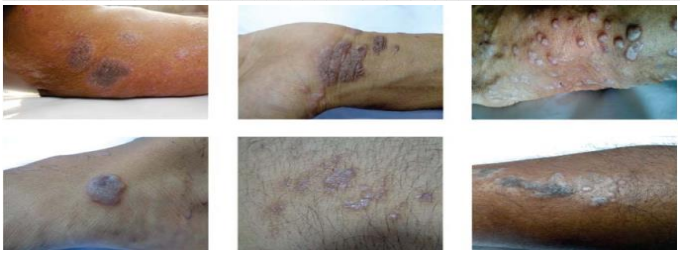

Fig 1: Plaque psoriasis (Case 1)

Clinically, psoriasis appears as raised, well-defined erythematous plaques with uneven borders and silvery scales. It has a comparable impact on the upper and lower extremities but has an affinity for the elbows, knees, head, and lower trunk as shown in Figure 2. Psoriasis is a papulosquamous skin disorder. Psoriasis vulgaris, frequently called plaque psoriasis, is responsible for around 90% of instances when the illness reveals itself dermatologically. Nail involvement, however, can occur in association with various other psoriasis, including guttate, inverted, erythrodermic, pustular, and palmoplantar psoriasis. Plaque psoriasis is defined by the appearance of elevated areas of inflammatory skin covered in silver-white scaly patches. Plaques are simply elevated areas of skin. Psoriatic erythroderma, also known as erythrodermic psoriasis, is usually caused by an exacerbation of unstable plaque psoriasis, particularly if systemic glucocorticoids are abruptly withdrawn. The outward appearance of the affected skin is frequently used to diagnose psoriasis.

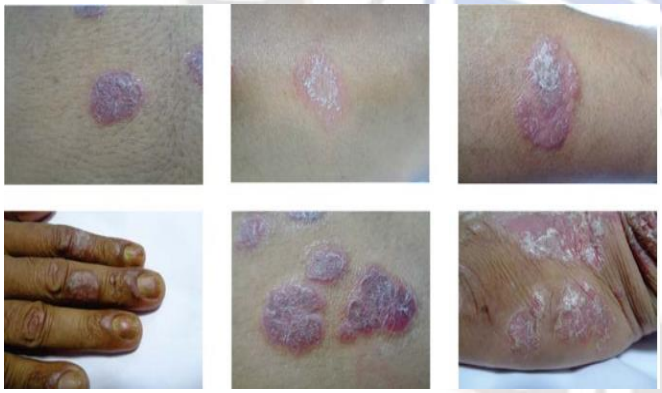

Fig 2: Plaque psoriasis (Case 2)

Psoriasis is a skin disorder characterized by scaly, pigmented plaques, papules, or spots of skin that can be painful & unpleasant. A reddish-pink appearance is one of the skin's additional qualities. With the use of specific blood tests or other diagnostic techniques, the diagnosis could be made. If the clinical examination cannot conclusively diagnose the illness, dermatological biopsy or scrubbing may be performed to exclude other medical problems and aid in the diagnosis. Under a microscope, a skin sample will reveal malformed epidermal outgrowth that becomes interconnected with the dermis. Several distinct histopathological features distinguish psoriasis lesions. Epidermal thickening makes up one of these observations.

The following is the papers content: Section II will discuss the related work. In section III, proposed work with its framework and its methods are discussed. In section IV, results and discussions are presented. Finally, section V, will conclude the work with final remarks.

II. RELATED WORK

Dermatological diseases are often diagnosed clinically through histology and clinical patient evaluation. The medical professional's degree of knowledge will determine how effective this diagnosis will be. However, there is a risk of inconsistency in the clinical assessment, particularly in information, quantification, accuracy, and data consistency. Histopathology is a time-consuming and inconvenient test that also necessitates a high level of knowledge in the area. As a result, developing novel procedures is required to enable the easy and rapid identification of skin diseases. Computer-aided diagnosis offers a different approach to this issue. There are currently few clinical diagnostic methods that depend on distinctive characteristics.

In the following section, we will summarize the present research that is relevant to the topic, as well as connected datasets and issues. The majority of cancer of skin classification algorithms now in use rely on individually produced variables such as lesion type (primary morphology), lesion configuration (secondary morphology), color, dispersion, form, texture, and border irregularity observations [8]. Following the extraction of the features, methods based on ML models for classification tasks with promising results [9]. Here are a few cases of similar work incorporating hand-crafted features and popular classifiers: [10] Colour histograms, edge histograms, and numerous scales of color local binary patterns (LBP) were employed as hand-coded feature extraction methodologies. In the course of the research, these strategies were applied.

In [11], the authors constructed a unique psoriatic significance grading using psoriatic images of Asian Indian origin. A machine learning framework for risk classification of psoriasis disease phases was developed using offline instruction and online evaluation images. They generate four types of pRAS systems. It accomplishes this by employing two distinct types of classification algorithms (support vector machines, or SVMs, and decision trees, or DTs), both during the training and testing phases, as well as two different types of selection of features, resulting in an entirely comprehensive evaluation of the four systems mentioned previously. When the cross-validation strategy and the K-fold methodology are used, pRAS, which implements (SVM + FDR) amalgamation, obtains a success rate of 99.92%. The assumptions and hypotheses were met by

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computing a wide range of metrics for performance assessment, including element retention power, combined component impact, and system dependability. The findings provide hopeful prospects, and the pRAS system demonstrated its ability to stratify the psoriasis condition effectively.

In [12], the authors created a psoriasis lesion diagnostic method to simplify the task of the medical professional in diagnosis by delivering better and more trustworthy findings to assist the physician's choice in diagnosing the lesion, particularly physicians with limited expertise. They concentrated on psoriasis lesion diagnosis utilizing color and texture characteristics, and they discovered a novel sign (color and texture features) deployment to assist choice. The database utilized an average of 200 picture samples from people with psoriasis. Machine learning employs the ANN to achieve optimal results for color-texture features using the RGB-Local Binary Pattern and RGB Color Co-occurrence Matrix method.

In [13], the authors presented a novel algorithm based on CNN for skin segmentation affected by psoriasis. Later they applied preprocessing step, and the submitted visuals were split up using an adaptive Chimp optimization algorithm (AChOA)/CNN model, with the bias and weight parameters of CNN changed using AChOA's supervision. Adjusting the unpredictable series based on the tent map improves AChOA's search capacity. After completing everything, the segmented output images submit to the threshold module to remove any artifacts. The results achieved show 97% accuracy as related to other models.

In [14], the author intends to develop a psoriatic plaque diagnostic system to simplify the physician's role in the diagnosis process by providing more accurate and superior results. These findings are designed to corroborate a specialist's choice for diagnosing the lesion, making them particularly valuable for physicians without knowledge. The database we use contains 220 psoriasis image samples, 70 of which are healthy, 50 of which show diverse skin lesions, and 100 of which indicate illnesses. Machine learning techniques are applied to achieve the highest possible efficiency. With an average precision of 90.9%, a sensibility of 86.9%, because the CADx system has evolved into a mission for medical professionals, it is vital to have a CADx system that is accurate and dependable. Psoriasis is a condition that can be precisely identified by observing the displayed texture. Experiments with all of the previously described feature combination models revealed that combining color and texture carried about more accurate results than each feature alone.

In [15], the authors provided a severity scale evaluation technique for dual psoriatic skin pictures. We extract lesion features, especially utilizing the bag-of-visual-words (BoVWs) model. The BoVWs concept revolves around developing a glossary with a certain amount of words utilizing a clustering approach and some local attributes acquired from a collection of crucial locations. This is performed by using the phrase "codebook size." The following phase will use support vector machines (SVM) and random forests (RF) as a 3-class classification. They used eight texture and color descriptors, and orientation histograms are all condensations for the same. The following stage combines color and texture identifiers; the final step is to characterize the texture. Furthermore, the K-means method produces more accurate results in vocabulary construction than the GMM algorithm and operates in less time. Finally, when assessing the severity of a scale, the proposed approach achieves an accuracy of 80.81%.

Most of the study's conclusions have yet to be checked by dermatologists; however, to overcome these limits, a dermatologist-developed the current study and monitored all procedures. Separate image collections were taken for the training and examination sets, and the maximum potential lesions were isolated from each without a single instance of duplication. We selected three diseases for this study because they might produce different diagnoses compared to one another. Finally, the clinical diagnosis technique was evaluated, and significant features were extracted using the most suitable algorithms.

III. THE PROPOSED WORK

In the current study, a database is developed, and then computerized image preprocessing, segmentation, feature extraction and classifications are used for building a skin disease classification system. Dermnet's dataset was investigated for images of skin diseases to use in this study. This data was subsequently separated into two datasets, the training and testing sets. The images in this dataset were used to build an intelligent tool that can diagnose three different skin diseases. We upgraded images from both sets utilizing an array of methods to obtain higher levels of quality. Image cropping and segmentation algorithms were used to identify malignant lesions in healthy skin. In the final stage, feature extraction algorithms were utilized to determine a practical course of action by isolating the clinically relevant individual features. Both the training and testing sets of features were used to train the system for classification. The tool's effectiveness was then tested and verified using the testing set. Figure 3 illustrates the proposed framework of the method that was used in the study.

Dataset

Images of 23 different skin illnesses are included in the collection of images, which can be found at http://www.dermnet.com/dermatology. There are around 19,500 images, with approximately 15,500 in the training set

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and the rest in the test set. These images are in JPEG format and have three separate channels designated by the letters RGB. Although the resolutions differ between images and classes, they are not high-resolution images. Pimples, melanoma, Eczema, Seborrheic Keratoses, Tinea Ringworm, Bullous disorders, Poison Ivy, Psoriasis, arterial tumors, and other ailments are covered.

Preprocessing

The following stages are included in the preliminary processing of uploaded images: (i) adjusting the values of the pixel to a range of 0 to 1; (ii) resizing the image to the square measurement (if necessary); and (iii) scaling the image to the desired size of 224 by 224 pixels. The image processing toolkit is used for noise filtering, which removes unwanted sounds from images and filters out unnecessary information. Contrast stretching improves image contrast by extending the intensity scale to fill the whole dynamic spectrum. This is done to improve the contrast of the image. The modification function remains linear, and its expansion is constant and stable. Figure 4 depicts a standard modification algorithm for intensity stretching.

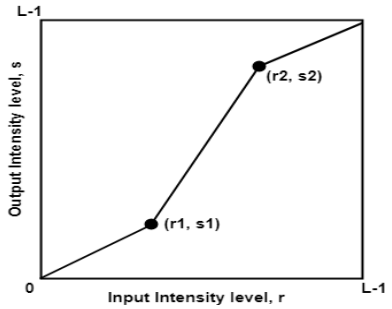

Figure 4: Transformation function used for Contrast Stretching

We can change the shape of the reconfiguration function by rearranging the points (r1, s1) and (r2, s2) in the coordinate system. When r1 and r2 are equal, the transformation transforms into a linear function. The transformation function becomes a thresholding function when r1 and r2 have the same value and s1 and s2 are zero. Min-Max Stretching" refers to an instance in which (r1, s1) equals (rmin, 0) and (r2, s2) equals (rmax, L-1). "Percentile Stretching" refers to the scenario in which (r1, s1) equals (rmin + c, 0) and (r2, s2) equals (rmax - c, L-1).

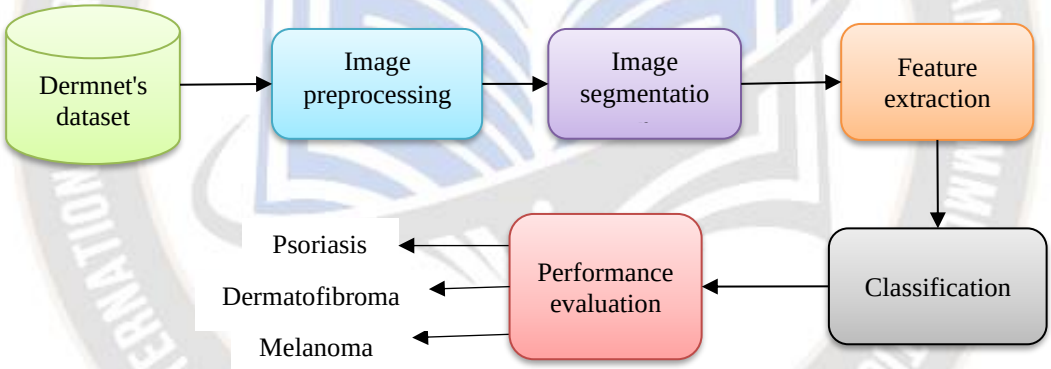

Figure 3: The proposed framework of the method

Segmentation

The fuzzy c-mean technique is among the most often used image segmentation algorithms. This method divides a picture's space into several separate cluster sections, each with equivalent pixel values in the image. The fuzzy clustering method is the most effective for medical image segmentation. In this section, we will provide an updated version of the fuzzy c-mean algorithm:

Step 1. Assume that the variable *H* represents the frequency of occurrence of each item in the data.

Step 2: Create a vector I = min (Data): max (Data).

Step 3: Choose the centroid of at least two of the locations at random.

Step 4: compute the membership matrix.

Step 5: Determine the cluster centroid.

The proposed technique does not rely on the image's overall data, but rather on the data which indicates the frequency of each particular data item.

Feature extraction

Feature extraction is also known as the Convolutional Neural Network (CNN) or Deep Learning Feature Extraction. It is an operation that includes the tasks of image pre-processing (normalization), image segmentation, essential feature extraction, and class identification. These tasks are part of the entire operation.

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MobileNet Design Model

MobileNet topologies are based on replacing complex convolutional layers with more basic ones. Each layer in mobileNet designs comprises a 3×3 convolutional layer that filters the incoming data, followed by a 1×1 convolutional layer that combines the filtered parameters to create a new component as shown in Figure. This reduced model aims to outperform more traditional convolutional models regarding processing speed. The MobileNet design is appropriate for mobile devices and computers with low computing capacity because it takes less processing than the classic CNN model. This is the crucial advantage of using the MobileNet architecture. This model can also be used to segregate data dependent on two accessible features that efficiently transition between the accuracy and latency of the parameter. This layer can be used for dividing the data because it is based on two convenient features. The MobileNet concept has various advantages, one of which is that the network's size is minimized.

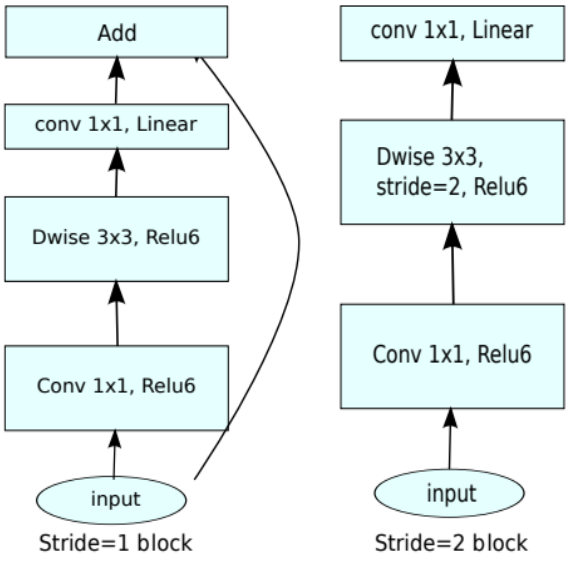

Figure 5: Architecture of MobileNet V2 model.

The MobileNet V2 structure also includes a residual layer with a stride of 1, a downsizing layer with a stride of 2. Each residual is composed of three sub-layers in total:

• The first layer is a 1 × 1 fusion performed with the ReLu6. The second layer of the pattern is known as Depth-Wise Convolution.

The proposed design consists of three layers, with the third being a 1 × 1 convolution layer with no non-linear dynamics. The ReLu6 component is employed in the structure's third layer's output realm.

• Using ReLu6 is critical for maintaining the framework's stability in low-precision states and improving system predictability.

• Within the framework of that overall sequence, each layer has the same number of output channels. We use dropout and batch normalization techniques throughout the training phase of modern architectural models. Furthermore, a type of filter with a dimension of 3×3 is commonly used.

There is a residual component that, through batch processing, helps to maintain gradient flow across the network, while ReLu6 is the activation component. This is the grey-level correlation matrix: we employ the GLCM strategy for texture feature extraction that can be calculated by arranging the intensity levels inside the window. We can represent this structure on a map. The GLCM algorithm focuses on tabulating the amplitude spectrum.

Classification

The secondary purpose of our research is to completely replace the softmax classifier (the topmost part of the model) in MobileNet V2 with dropout linear SVM. This was done to carry out the classification. We have proven that dropout SVM produces superior results compared to deep CNN using the softmax top layer. This also minimizes the possibility of overfitting the classification test output. SVM, or Support Vector Machine, is a linear model that can address data categorization problems. SVM is a powerful tool for dealing with a wide range of linear and non-linear classification problems. The most basic description of what support vector machines do is to find or compute a line that divides two distinct groups for every given instance. A support vector machine (SVM) is a type of algorithm that embraces data as its input and produces as its output an ideal line that differentiates between those classes. We initially designed SVM for linear classification; however, for the sake of our research, the SVM classifier must be capable of distinguishing between more than two classes. SVM may handle problems involving various class classifications by breaking down a single multiclass problem into numerous binary classification issues, which are then dealt with in the same way as a conventional SVM linear classification problem using a one-versus-all technique. The method that forms the one-versus-all strategy is the development of binary classification algorithms that can differentiate between one of the labels and the other classifications. The outcomes of SVM predictions are identical to those produced using the softmax function.

Proposed Flow Architecture:

Skin cancer image classification plays a vital role. The method reported here employed skin images to suggest a new approach for classifying three types of skin cancer, including psoriasis, dermatofibroma, and melanoma. As illustrated in Figure 6, this system divides its actions into separate stages, which are important for improving classification accuracy. This approach

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targets to provide a successful arrangement for classifying skin diseases.

Step 1: Input Image

For classification, a facial skin image is utilized.

Step 2: Pre-processing (Contrast Stretching, Noise Filtering)

Using an image processing toolset, noise filtering removes extraneous information and noises from images. Using an image processing toolset, noise filtering removes extraneous information and noises from images.

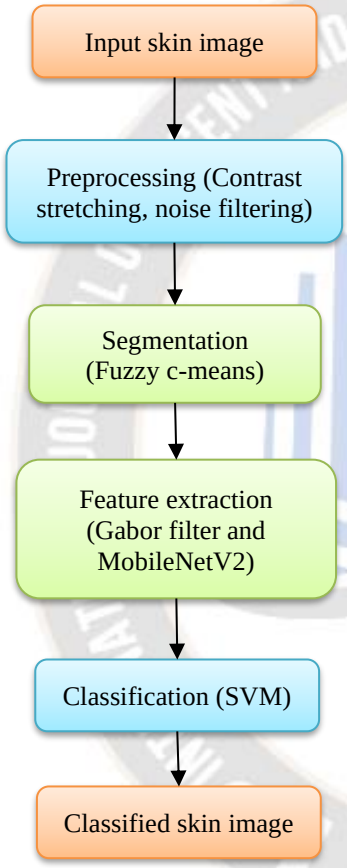

Figure 6: Classification framework of Skin Disease

Step 3: Apply Fuzzy C Means

Fuzzy C Means Used for Image Segmentation and Clustering.

Step 4: Feature Extraction Using CNN

GLCM, Gabor Filter, and CNN (mobile net) can extract feature vectors such as texture from input facial skin pictures. The RGB-coloured pictures are used to extract the texture element. The GLCM functions characterize an image's texture features by calculating the frequency with which pairs of pixels inside an image have given values. They are positioned in a particular spatial relationship. Furthermore, global color histograms are used to determine the color features of skin images. The core premise of MobileNet is to use depth-wise separable convolutions to build lightweight deep neural networks. When using a traditional convolutional layer, the convolution kernel or filter is applied to all the channels of the provided image. This is performed by employing the filter to compute a sum of weights on the input pixels and then moving on to the next input pixel across the images. This regular convolution is used only in the first layer of the MobileNet algorithm. Along with depthwise convolutions, depthwise separable convolutions are produced by combining depthwise and pointwise convolutions.

Convolution is performed on each channel separately using the depthwise convolution approach. As a result, if the input image contains three channels, the output image will also have three channels. The depthwise convolution filtering that occurs filters the input channels. The ordinary convolution is followed by the pointwise convolution, which is very similar but uses a 1x1 filter instead. This is the following stage. The depthwise convolution's output channels are combined with the pointwise convolution to produce extra features. This is precisely what pointwise convolution is aiming for. When this is done, the amount of computer effort required is far smaller than when typical convolutional networks are used.

Step 6: - Training and testing framework using SVM

The method that guides the Support Vector Machine uses element vectors (color and texture) to design and develop our suggested structure. Each image's color and texture features have been collected in a database, and these qualities will be employed in the subsequent phase of classification. Considering these component vectors, color, and texture, the proposed structure resulting from SVM would classify the skin images into various classes. To obtain an accurate classification, several distance metrics are used to measure the degree to which an image's features are comparable to those of other images. SVM classifiers were used in this case to assess the similarity between the qualities of the Query Image and the attributes of the database images. The SVM classifier will generate the input image's feature value, which it will then compare to the actual value of the feature in the database images. Based on these parameters, the SVM classifier will finally decide the class of the input image.

IV. RESULTS AND DISCUSSIONS

In this section, all clinical images are used solely for training all algorithms. Mobilenet's development was effective in obtaining optimum performance. The algorithm was then pretrained with data from other body parts, and we used the set of parameters from the pre-trained model as the initial parameters for the newly developed model using a transfer learning approach. We employ Matlab 2019a to carry out the simulation tasks.

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Figure 7 shows the input image provided by the user for further processing of an image. Figures 8-10 shows the all the process of classification of skin diseases.

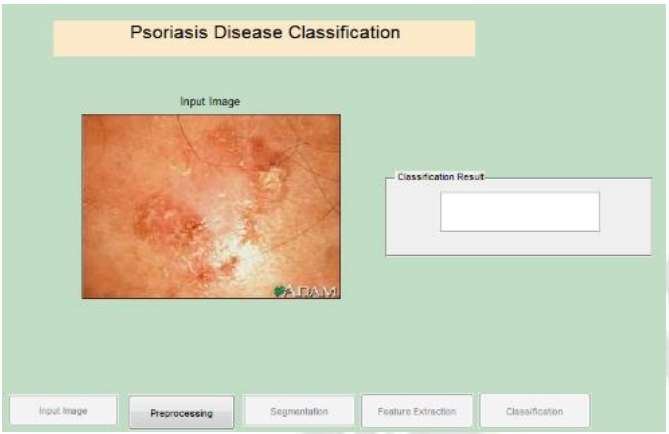

Figure 7: Input image

Figure 8: Pre-processed image

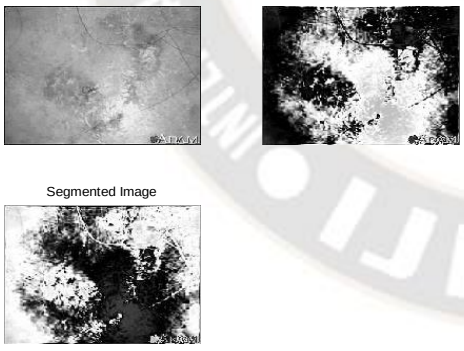

Figure 9: Segmented image

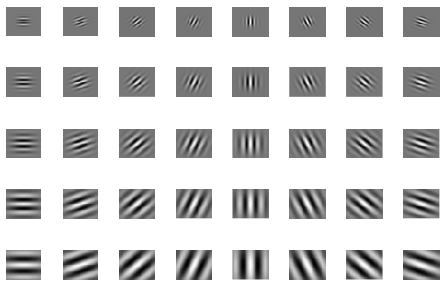

Figure 10: Extracted features image

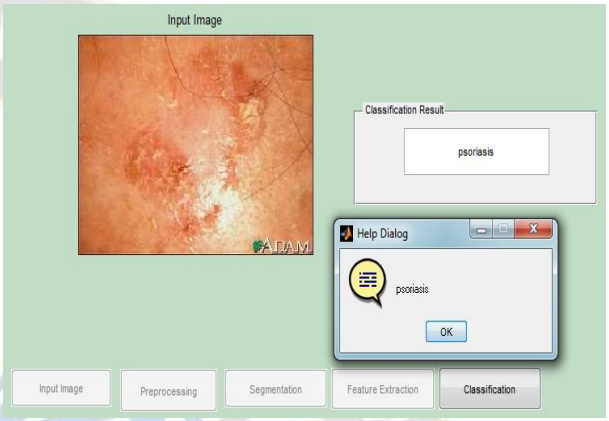

Figure 11: Classified image

Table 1: Results of model for 3 different skin disease before feature extraction

Class	Precision	Recall	F1-score
Psoriasis	89.65	84.24	98.21
Dermatofibroma	88.14	87.24	88.35
Melanoma	89.21	87.32	88.87

Figure 12 shows that Psoriasis disease is classified with the highest F1-score of 98.21% on the DermNet dataset. Similarly, Dermatofibroma has the lowest F1 score of 88.35%.

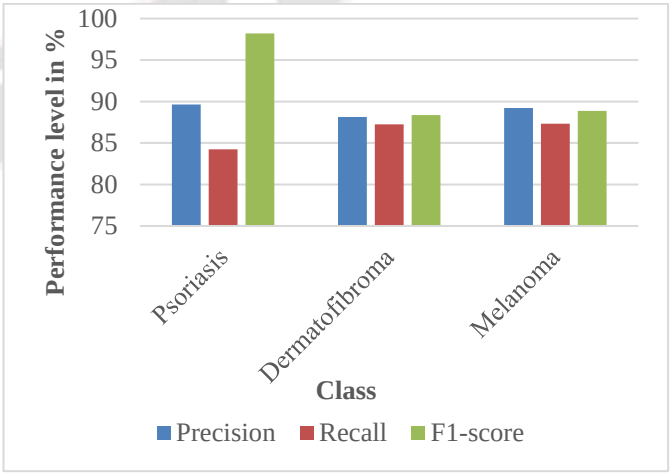

Figure 12: Performance comparison of three classes without feature extraction

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Table 2: Results of model for 3 different skin disease after feature extraction

Class	Precision	Recall	F1-score
Psoriasis	98.65	98.42	98.66
Dermatofibroma	98.14	97.24	98.35
Melanoma	99.11	97.32	98.73

Figure 13 shows that Psoriasis disease is classified with the highest F1-score of 98.66% on the DermNet dataset. Similarly, Dermatofibroma has the lowest F1-score of 98.35%. This shows that after applying feature extraction, the false positive is reduced to 10% in all three tasks.

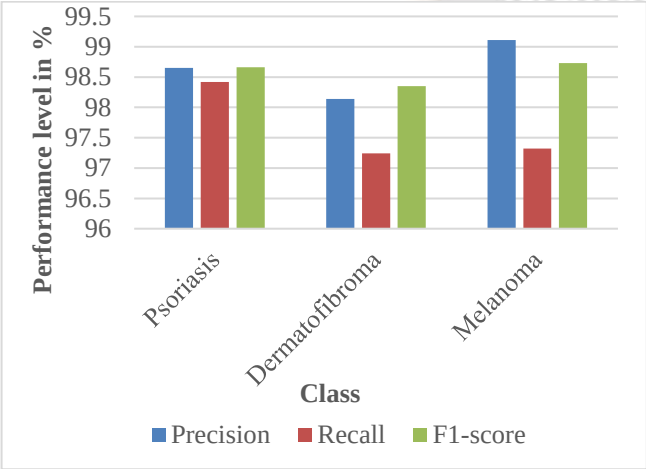

Figure 13: Performance comparison of three classes with feature extraction

Figure 14 depicts the efficiency of several algorithms that can be evaluated. The authors of [16] proposed a CNN classifier for use in diagnosing the source of skin problems using the DermNet dataset, and their results obtained an accuracy of 98.6%. Using the DermIs, DermQuest, and DermNZ DermNet databases, the authors of [17] developed an SVM classifier for detecting skin disorders. They were capable of reaching an 83% accuracy. The authors of [18] proposed a QSVM classifier for detecting skin disorders using the datasets DermIs, DermQuest, and DermNZ DermNet. With this classifier, they attained an accuracy of 94.74%. The authors of [19] proposed a CNN-SVM classifier for detecting skin diseases. They achieved an accuracy of 86.21% by using three datasets: DermIs, DermQuest, and DermNZ DermNet. The authors of [20] recommended a CNN classifier for detecting skin disorders using the DermNet dataset. Using this strategy, they achieved 70% accuracy. On the other hand, our suggested study used MobileNet V2 in conjunction with the SVM DermNet dataset and attained an accuracy of 99.12%.

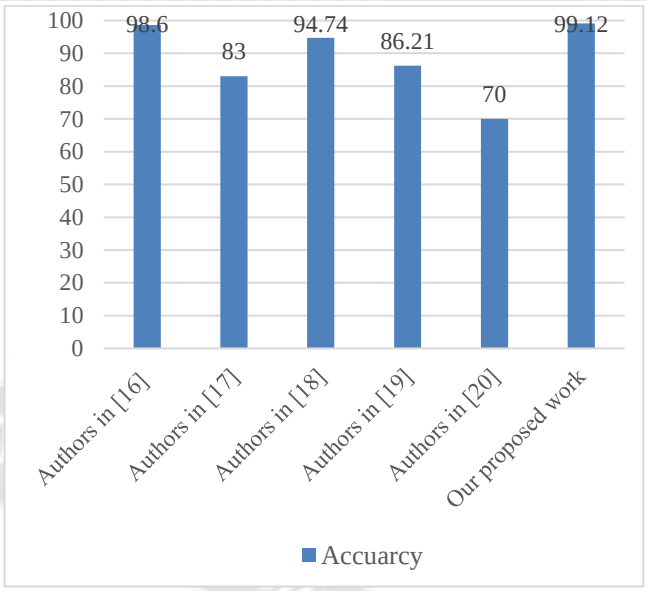

Figure 14: Performance comparison of different algorithm works

V. CONCLUSION

Presently, the paper has laid out a study on the performance of computer-aided diagnosis (CAD) methods for classifying skin images using different features. Using images as the primary diagnostic tool, this study demonstrates an effective technique for identifying three widespread dermatological diseases using three steps (i) Input images must be preprocessed for contrast stretching, noise filtering, and fuzzy C-means for image segmentation and grouping. This is essential to achieve best results. (ii) A support vector machine (SVM)-based classification approach has been presented, and the images provided show only lesions rather than whole images. (iii) A pre-trained MobilenetV2 model with a new loss function was used in this evaluation. According to comparative evaluations, the MobileNetV2 architecture provides results with the best recall (98.66%). Compared to other architectures, this architecture has superior precision and recall values.

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