Identification of Skin Disease Using Machine Learning

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Abstract. Skin diseases are a serious health issue that affects a large number of individuals. In recent years, with the fast advancement of technology and the use of various data mining approaches, dermatological predictive classification has become increasingly predictive and accurate. It is more helpful to dermatologists to identify the disease, As a result, the development of machine learning approaches capable of efficiently the purpose of this study is to make an application of identification of skin disease images by using the machine learning method, Support Vector Machine (SVM), and KNN techniques. Early detection of skin diseases is performed using image processing and machine learning. This study aims to determine the classification of skin diseases in humans. Each skin disease has symptoms. It has five skin diseases, such as acne, psoriasis, wrath, psoriasis, and ulcers. We have collected 314 skin disease images from the government hospital in Aurangabad with the help of a mobile camera and a Sony HD camera. A Gaussian filter is used for image pre-processing. The segmentation method is used for K-Means Clustering and the feature extraction method is used for feature extraction. We have used the haar feature, color feature, FCM, OS-FCM, GLCM, and LBF features for classifications. Based on the result, the SVM is given 92% accuracy for haar feature, FCM, and OS-FCM. And the KNN classifier and K-Means are given 89% and 89% accuracy using a mobile phone camera dataset.

Keywords: Skin Disease · K-Means Clustering · SVM · KNN · Color Feature · Texture feature · Haar Feature

1 Introduction

The skin is the outer layer of the body. It is frequently exposed to the environment, where it may come into touch with dust, microorganisms, and UV radiation. These might be the causes of any disease. Skin-related disorders are made more complicated by genetic instability [1, 2]. The skin is connected to several skin diseases, affecting

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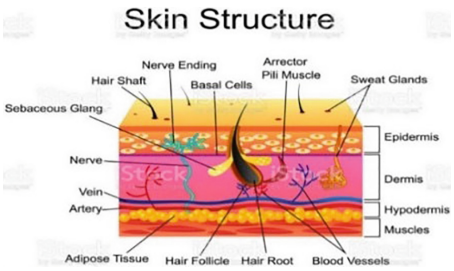

Fig. 1. Anatomy of skin in Human Body.

a person's appearance and capacity to operate. Skin infections are caused by bacteria, fungi, or viruses [3]. As represented in Fig. 1, the human skin has three layers, such as the dermis, epidermis, and hypodermis. The major causes of skin diseases are the most common causes of skin diseases, such as fungal infection, bacteria, allergies, viruses, and other factors. When conditions like infections or chronic diseases are prevalent, the texture or color of the skin generally changes. Skin infections must be identified early to avoid development and spread. It damages the patient both financially and physically [4]. Because of its complexity, dermatology is one of the most difficult fields to diagnose. The widespread use of smartphones in developing countries has opened up new opportunities for low-cost early disease diagnosis. We are obtaining image processing skills for device diagnostics using smartphone and digital camera technologies. We created an application that takes a two-stage approach to solve problems. Machine learning was used in the second step to offer a solution, while image processing was employed in the first stage to detect the issue [5]. The difficulty for the patient to diagnose is that a condition that appears to be a feature of one disease in the early stages may turn out to be a sign of another in later stages. Some disorders need medical attention, yet they all have common flaws. As a result, a dermatologist trained a machine learning model on the assessed properties obtained by a microscope analysis of a skin sample to tackle this challenge.

The key conclusion of this study: The key conclusion of this study: Create a database of images of various skin diseases. ii) A comparison with a mobile phone camera and a digital Sony HD camera.

2 Related Works

Recently, The study of enhanced technological advancement in combination with digital image processing for disease classification. The SVM-based supervised learning system, multi-model, and multilevel technique for analysis were employed by the researchers to identify eczema [6]. Based on the hue of the fingernails, the SVM was used to identify various circulatory infections [7]. Using melisma images as a diagnostic tool, infections were identified [8]. This shows that a method of determining BCC was offered (Basel Cell Carcinoma). The system is capable of accurately recognizing the. Existence of basal-cell carcinoma using adequate thresholding values with a percentage reliability of 91.33 percent in the detection. Three different skin problems keratosis, pyoderma,

Table 1. Different Types of Skin Disease.

Disease Name	Types of Disease	Images	Symptoms
Viral skin Disease	Eczema, Psoriasis, Vitiligo, Hive, Impetigo,	Babies, Plantar warts in adults,	Signs of viralinfection1.cryin, excessive
Fungal Skin disease	Rosacea, lupus, Vitiligo, Melisma	Fungal infection is caused by men and women	Skin changes, red and Possibly
Pigmented skin Disease	Vitiligo, melanocytic, naive (mole), seborrhoea keratosis, skin cancer, melanoma.	There are different categories of pigmented skin benign,	Vitiligo is a condition that causes patches of light skin.

and dermatitis are selected for segmentation using the suggested method, which uses the Sobel operator [9]. Color and texture characteristics and 4,182 color and texture attributes were the two feature sets tested. The average F-measure for the 86 features was 86.67 percent, and for the 4,182 features, it was 84 percent, which was a promising result. As a classification method, the building of an SVM has split the dataset into different classes. Using this method, three groups of skin disease images were categorized skin lesion segmentation, ABCD rules, and GLCM. With the help of KNN, Random Forest, and SVM, the data were categorized. The classifier had a high accuracy of 89.93% when the ABCD Feature Extraction was performed [10]. The literature has made substantial progress in the detection of skin diseases. However, the suggested approach is primarily intended for the identification of a single form of skin disease, making it difficult to apply to the exact identification of many types of skin diseases. We found that even though there is limited research on using one method to describe two or more diseases.

Segmentation, GLCM, color extraction, LBF technique, SVM, KNN, K-Means algorithms, and machine learning-based algorithms to determine whether the skin lesion is useful in the diagnosis of various skin diseases using two different.

Resolutions such as camera photos and Mobile phone images. Diagnosis of skin conditions from a picture is a difficult challenge. There are so many different types of skin disorders, such as acne, psoriasis, eczema, leprosy, wrath, ringworm, and vitiligo. It is presented in Table 1. Challenges: The disease has many skin lesion types. Many diseases may have similar characteristics, which is often confusing for the dermatologist.

3 Method and Techniques

3.1 Input Images

We can take images from the government medical hospital in Aurangabad. We collect photographed patient disease images while dermatologists'. To identify images from the clinical dataset, we have taken five types of skin disease datasets such as acne, psoriasis, eczema, warts, and ulcers (Fig. 2).

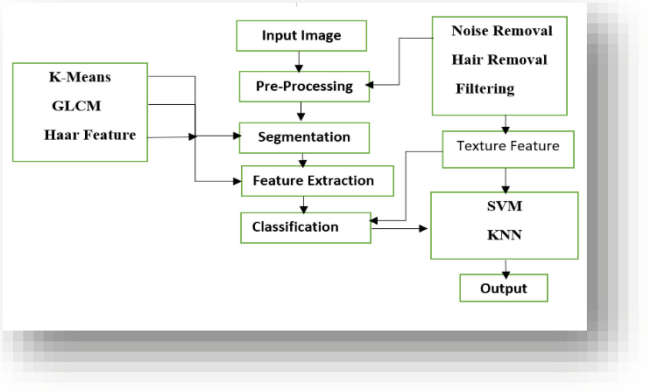

Fig. 2. Block Diagram of Proposed System.

3.2 Image Preprocessing

Improving image quality in the preprocessing step begins with removing unnecessary noise. Hair and bubbles may appear as noise inside the picture photograph. It becomes necessary to filter the picture to remove noise, and some photos contain an undesired feature that is sometimes present in dermoscopic images: hair. Because noise affects categorization accuracy. In this paper, we used filters such as Gaussian filters, adaptive filters, and Median filters for denoising, which include Gaussian noise, salt and paper noise, passion noise, and speckle noise. We go into greater detail about this in previous papers. A Gaussian filter is used to reduce noisy images (Table 2).

The tests were carried out on a variety of standard photographs of various resolutions. Python programming is used to carry out the reproduction. The information is tainted by the harmful impacts of replicated Gaussian, salt and paper noise, speckle noise, and Poisson noise. As the PSNR lowers, the MSE increases, and vice versa. When the peak signal-to-noise ratio increases, the resulting image becomes highly smooth to the eye's perception, and the image returns to its previous state. Images that are highly deformed have a high value.

3.3 Filtering Techniques

To acquire the denoised image and determine the MSE, PSNR, and Entropy values, we applied Gaussian, Median, and Wiener filters to de-noised images on the noisy image.

The MSE, PSNR, and entropy of each examined filter, namely Gaussian, Median, and Weiner filters, are shown in Table 3. Gaussian, speckle, salt, and paper noises were all removed using each filter. On the Gaussian noise, the Gaussian filter performs better than other filters, with 18.67 MSE, 12.81 PSNR, and 5.26 entropy values. On salt and pepper noise, the Wiener filter is given high values, such as 31.56 MSE and 29.10 PSNR.

Table 2. Impact of different Noise types over Image set of Diseases.

Disease Name	MSE	PSNR	Entropy	Noise
Acne	53.67	22.651	7.75	Gaussian Noise
Psoriasis	41.20	38.25	8.26	
Ulcer	31.25	36.58	6.89	
Eczema	51.26	28.96	7.63	
Acne	59.76	20.30	7.05	Salt and Paper Noise
Psoriasis	56.26	51.02	7.49	
Ulcer	32.33	36.92	6.96	
Eczema	49.23	27.70	6.36	
Acne	58.73	27.49	7.43	Poisson Noise
Psoriasis	63.21	59.69	7.52	
Ulcer	36.44	38.24	7.26	
Eczema	33.36	29.63	7.25	
Acne	56.76	20.92	5.48	Speckle Noise
Psoriasis	52.02	49.51	6.89	
Ulcer	32.69	36.41	7.37	
Eczema	33.22	28.63	7.44	

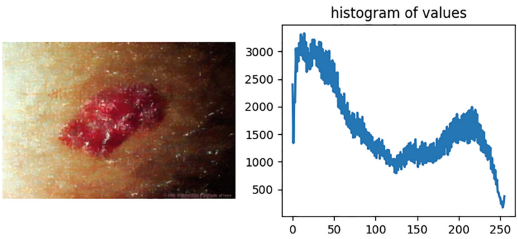

Fig. 3. Detection of Noise using Histogram.

3.4 Gaussian Filter

The image was smoothed and the noise from the artifact was removed using the Gaussian filter, for the influence detected and brought about by an irrelevant backdrop of pictures, a Gaussian filter is required. It is a common method for removing salt and paper noise from photos while preserving edges and being helpful in their creation [11]. A Gaussian filter is a smoothed pixel according to the power-to-power coefficients. The smoothing function can be expressed in an equation.

PSmooth

$$(X, Y) = (C_{NormalA} + C_{NormalB})$$

Table 3. Filter Applied on Noise and Calculated PSNR, MSE, and Entropy values.

Various Filter	MSE	PSNR	Entropy	Name of Noise
Gaussian Filter	18.67	12.81	5.26	Gaussian Noise
	30.81	27.49	5.59	Salt and pepper Noise
	27.84	26.42	6.51	Speckle Noise
Median Filter	20.06	23.64	6.37	Gaussian Noise
	30.32	27.85	6.69	Salt and pepper Noise
	23.98	16.11	7.27	Speckle Noise
Wiener Filter	18.92	15.57	7.44	Gaussian Noise
	31.56	29.10	5.60	Salt and pepper Noise
	18.90	15.58	6.87	Speckle Noise

Table 4. Comparisons of original and filter MSE, PSNR, and Entropy.

Noise	Original MSE	Filter MSE	Original PSNR	Filter PSNR	Original Entropy	Filter Entropy
Gaussian Noise	44.35	23.13	31.61	20.08	6.80	5.07
Salt & Paper Noise	49.40	28.45	33.99	24.53	6.97	5.11
Poisson Noise	47.94	27.44	38.87	25.69	7.63	5.13
Speckle Noise	43.67	26.32	33.76	23.24	7.37	5.51

$$\sum_{in=-2}^{2}\sum_{ik=-2}^{2}\left(C_{i,jA}+C_{ijB}\right)P_{row}(X+i,y+j) \tag{1}$$

where PSmooth (x, y) and P_row (X + i, y + j) denote the raw pixels, respectively. Represents the approximation Gaussian coefficient(C normal and normal), representing the normalized coefficient. Gaussian noise is found in most skin disease images. We used a Gaussian filter for the removal of the noise and we got better accuracy in MSE and PSNR. Even if the skin disease image displays a better-enhanced image, the PSNR values do not interpret comparable findings, and it is easy to help evaluate them. Table 4 tabulates the average PSNR and MSE values for each tested filter, as well as the computed MSE, PSNR, and entropy. Each filter is applied to remove the Gaussian, salt and pepper, and speckle noises. The Gaussian and Median filters outperform salt and pepper noise when comparing the three filters for speckle noise. Furthermore, the median filter outperforms other filters in terms of PSNR and MSE, but only for salt and pepper noise density levels of less than 30%. Among the others, the Gaussian noise and

Gaussian filter provide great accuracy MSE is given high values in every skin disease, and PSNR is given less than MSE values.

3.5 Image Segmentation

An important component of image recognition is image segmentation. The purpose of picture segmentation is to divide an image into different sections to identify which areas need more attention than the surrounding areas [12]. The K-Means Clustering method is used to segment the skin disease image. Depending on how close the data is to each cluster's centroid, this approach separates the data into different cluster areas. The image segmentation process produces a picture with border detection in the foreground.

The image segmentation with K-Means Clustering results in Fig. 3 is subjected to the post-preprocessing stage. Because these findings are considered less than ideal and could include noise or small things. The method makes use of binary image processing techniques, including the Gaussian filter, noise reduction, border cleaning, the masking process, and cropping images of skin disorders. The post-preprocessing stage is performed on the image segmentation with K-Means Clustering findings in Fig. 4. Since these results are regarded as less than ideal and may contain some noise or small objects. The approach employs binary image processes such as the Gaussian filter, noise reduction, border cleaning, the masking process, and cropping photos of skin conditions.

3.5.1 Contrast

$$A_1 = -\sum_{I}^{L-1}\sum_{I}^{L-1}(G(i,j)2.Log(G(i,j))) \tag{2}$$

whereas G(i,j) is the distribution probability mostly employed in specified in the degree of depth computational mathematical approaches, and I refer to the grey level difference between neighboring pixels. The deeper the groove, the higher the contrast value.

3.5.2 Entropy

$$A_2 = -\sum_{I}^{L-1}\sum_{I}^{L-1}(G(i,j).Log(G(i,j))) \tag{3}$$

where A2 refers to the entropy, which means the quality of information that the image can change with the different textures. The texture of the speck would be sparsely distributed as A2 increased, as shown in Table 4, and vice versa.

The haar features used in Voila and Joneses exhibit a rectangle structure that consists of four subs in a rectangle. Some examples can be seen below. The integral image f is

Fig. 4. Image Segmentation Process.

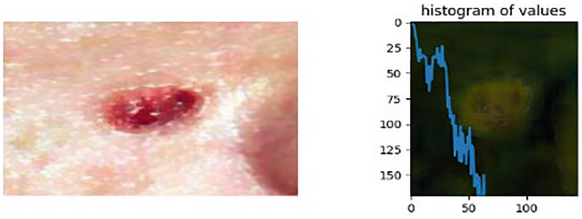

Fig. 5. Haar feature using a histogram.

denoted as Eq. 3 and Fig. 5. The integral F value at position [x, y] is calculated using the sum of the equation of I, which takes into account all pixels inside the rectangular range [0, 0] up to and including [x, y] [17]

$$f(x, y) = \sum_{a=0}^{x} \sum_{a=0}^{x} I(a, b) \tag{4}$$

The system was trained using 90 photographs from each group to create the training set, and the remaining 10 images from each group were utilized to create the testing set. Using BCC Images, the Haar feature was applied.

We made a conscious effort to display photographs with various dermoscopic image abnormalities when presenting the results. Figure 5 shows a dysplasia nevus with a lesion in the disease region and a boundary indicating the disease region.

3.6 Support Vector Machine (SVM)

The SVM is a machine learning technique that learns by using statistical theory [13]. When compared to other machine learning algorithms in the literature, SVM performs better than others. SVM handles limited quadratic differentiation between two classes, and it can also solve multiclass problems. The SVM method optimizes the distance between data points and hyperplanes. The Support Vector Machine, Fig. 5, is shown below.

Of all the kernels that are accessible, a linear kernel is also among the simplest. Other kernels, such as polynomial kernels, should be used to categorize two classes that share more characteristics to attain more accuracy and precision [14]. The boundary values of the SVM are specified by a gamma kernel [15]. This entails determining the inner products of a fresh input vector (x) with all training data's support vectors [16].The SVM receives all the values that were entered into the database as described as input (Fig. 6).

3.7 K-nearest Neighbor (KNN)

The K-Nearest Neighbor algorithm, which is based on the Supervised Learning technique, is one of the most basic machine learning algorithms. When a new data point is added, the K-NN algorithm classifies it based on how similar the existing data is to it and stores it all. This means that as fresh data is generated, it can be quickly categorized using the K-NN method [17].

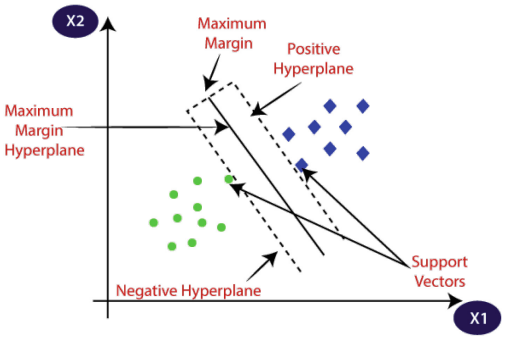

Fig. 6. Support Vector Machine using Linear Regression.

3.8 Feature Extraction

Four groups of human skin illnesses can be distinguished by several distinctive characteristics, including color and texture. For classification, these parameters were used.

3.9 Color Moments

Images of skin conditions can also be categorized according to how each class's colors vary. The color moments are the suggested technique for extracting color features. When describing the color of a picture, color serves as a reliable representation of color characteristics [18]. The color distribution of a picture is thought of as a probability distribution in color moments. Two moments from the color probability distribution of the image, including its mean and standard deviation, will be used in this investigation. The following equation can be used to compute the mean standard deviation.

$$E = \frac{1}{N}\sum_{J=1}^{N} P_{ij} \tag{5}$$

$$\partial_1 = \sqrt{(\frac{1}{N}\sum_{J=1}^{N}(P_{ij} - E_i)^2)} \tag{6}$$

In this research [15], the color method that was tested had the best accuracy in recognizing features of skin disease. The color space of YCbCr is a color space component (Y, Cb, and Cr) is a color that is applied in the photography system while Cb and C represent red and blue (Fig. 7).

We have used color feature, SVM, Hopkins, and Elbow techniques for the classification of skin diseases such as Eczema, Acne, Wrath, Psoriasis, and Ulcer. It has given different levels of accuracy in different skin diseases. As shown in Table 6, SVM is given good accuracy in the Acne (94%), wart (83%), eczema (92%), and ulcer (95%) disease, and the color feature is given 100% accuracy in Psoriasis disease. The mobile dataset is given the best accuracy in SVM techniques. Hopkins and elbow techniques give less results for skin disease.

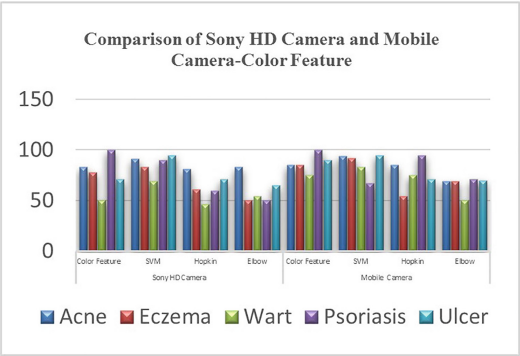

Fig. 7. Comparison of Sony HD Camera and Mobile Camera dataset.

3.10 Texture Feature Extraction

GLCM is an effective tool for analyzing texture features such as entropy and contrast. In this paper, nine different types of disease are chosen as the main research objects, which are acne, psoriasis, leprosy, eczema, wrath, melisma, ringworm, vitiligo, and ulcer, skin cold, respectively, are extracted from photos of a government hospital (Fig. 8).

We have used texture features and techniques for skin diseases such as eczema, acne, wrath, psoriasis, and ulcers. As shown in Table 5, it has given varying degrees of accuracy in various skin diseases. The SVM is given the best accuracy for eczema at 100%, warts at 100%, ulcers at 95%, acne at 93%, and psoriasis at 89% in the mobile dataset.

```
Confusion matrix SVM:
 [[ 1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0]
 [ 0  0  6  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  2  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0]
 [ 0  0  0  0  2  0  0  0  0  1  0  0  1  0  0  0  0  0  0]
 [ 0  0  0  0  0  2  0  0  0  0  0  0  0  0  0  1  0  0  0]
 [ 0  0  0  0  0  0  4  1  0  0  0  0  0  0  0  0  0  1  0]
 [ 0  0  0  0  0  0  1  9  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  4  1  0  0  0  0  0  0  0  0  0]
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 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1]]
```

Fig. 8. Confusion matrix of SVM.

Table 5. Summary of Precision, Recall and F1-score for skin disease classification.

Disease No.	Precision %	Recall %	F1 score%
Acne	1.00	1.00	1.00
Acne Nod	0.67	0.67	0.67
Psoriasis	0.8	0.8	0.8
Eczema	1.00	1.00	1.00
Wrath	0.89	0.89	0.89
Ulcer	0.6	0.6	0.6

4 Performance Measures

For calculating classification performance metrics for skin diseases including accuracy, sensitivity, specificity, positive predictive value, and negative predictive value, confusion matrices are utilized. Information concerning current and anticipated categories can be found in a confusion matrix.

To prevent bias brought on by the uneven distribution of disease, we have additionally computed precision, recall, and F1 scores for each disease.

$$Precision = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalsePositive}} \tag{7}$$

$$Recall = \frac{\text{TruePositive}}{\text{TruePositive} - \text{FalsePositive}} \tag{8}$$

$$F - measure = 2.\frac{\text{precision.recall}}{\text{precision} + \text{recall}} \tag{9}$$

We have observed the result and we got 1 precision accuracy for Acne and, Eczema disease and less accuracy for Ulcer Ulcers (Fig. 9).

5 Result and Discussion

The classification outcome is significantly influenced by the train-to-test ratio. It has been found that the results get better as the size of the training set rises. According to research on the impact of train/test classification accuracy, an 80/20 train/test ratio produces the best classification outcomes. We found that excessive training might reduce accuracy as well. We not only performed classification but also took a step forward and tried to classify all 314 unique sub-classes as well. We found 100% accuracy for the Color Feature and Haar features in the training data and 99.4 and 97.23% accuracy in the test dataset. We have got less accuracy for texture features in the training and testing datasets, at 86.23 percent and 75%, respectively.

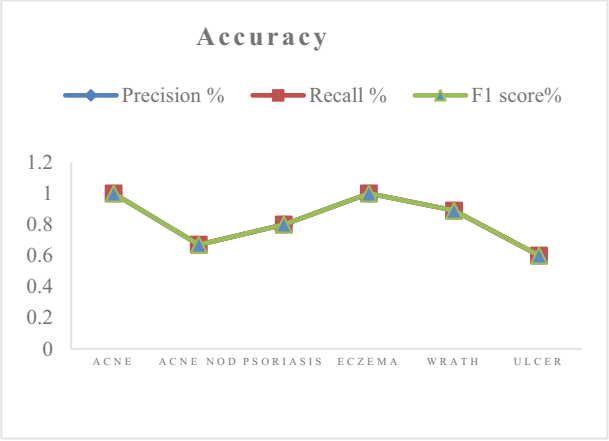

Fig. 9. Performance of classification

The color moment approach was used to extract color features from a variety of color spaces. The color spaces of the picture to be examined are RGB, HSV, and YCbCr. The three-color spaces are tested for correctness.

The RGB, HSV, and YCbCr color feature types exhibit the accuracy gained after the feature extraction experiment using the texture Moments technique in the color space. Color space eliminates the effects of light on the characteristics of skin color, allowing for the extraction of a wealth of feature information. Based on test results, some haar varieties are more accurate than others. The system produces high accuracy when applying multiple skin disease classes with the help of a mobile camera and Sony HD.

Camera resources the results show that the proposed system correctly identified patients' diseases. Acne, eczema, psoriasis, wrath, and ulcerative skin disease are all

Table 6. Feature Type of Skin Disease.

Disease Name	HD Sony Camera				Mobile Phone Camera			
	Texture Feature	SVM	Hopkins	Elbow	Texture Feature	SVM	Hopkins	Elbow
Acne	79	91	82	78	62	93	86	6
Eczema	56	89	67	72	63	100	62	62
Wart	31	85	46	46	25	100	25	75
Psoriasis	50	87	70	40	66	89	88	67
Ulcer	57	90	48	52	76	95	67	76

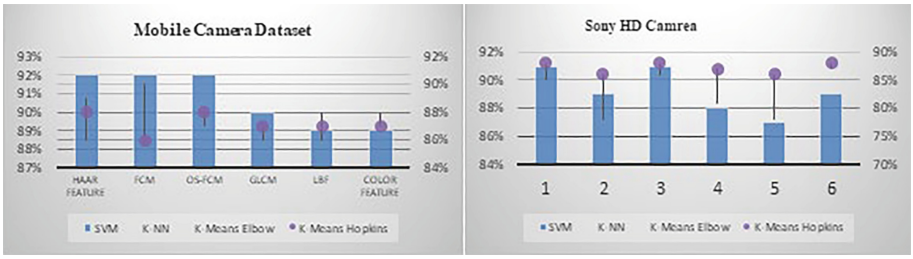

Fig. 10. Classifications Result of Mobile Camera and Sony HD Camera.

correctly identified by the system. We used different types of classifiers like SVM, KNN, and K-Means and used the Haar feature, color feature, FCM, OS-FCM, GLCM, and LBF features for classifications. The classification algorithm was developed to predict the diagnosis system. The Haar feature, FCM, and OS-FCM are given good results in SVM techniques for mobile camera datasets. The GLCM feature is given 90% accuracy in SVM. LBF and color features are given 89% accuracy in the SVM technique. The Sony HD camera dataset performed well in SVM for the Haar color feature, FCM, OS-FCM, GLCM, and LBF features, as shown in Fig. 10. A 92 percent accuracy rating is given to the suggested model. A substance score is also maintained by the SVM classifier.

6 Conclusion

The Research article focused on five skin conditions: eczema, psoriasis, acne, and ulcer. Gaussian noise and Gaussian filter preprocessing techniques are implemented for noise removal and image enhancement. SVM, KNN, and K-Means are used as classification for the features FCM, OS-FCM, GLCM, and LBF features for classification experimental analysis showing that better accuracy is obtained through SVM.

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