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# Analysis Toward Detection System of Skin Diseases (Impetigo, Melanoma, Diabetic Foot Ulcer, and Seborrheic Dermatitis)

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***Abstract*— Skin diseases vary greatly in symptoms and severity, so detection of such diseases is extremely difficult. In this research paper, three different comparison and analysis are done on two types of feature extraction methods: Gray-Level Co-Occurrence Matrix and Image Quality Assessment, three types of segmentation methods: Marker-controlled Watershed, Otsu Thresholding and K-Means, three classifiers: Linear Support Vector Machine, Non Linear Support Vector Machine and K-Nearest Neighbor for the detection of four different skin diseases namely, Impetigo, Melanoma, Diabetic Foot Ulcer, and Seborrheic Dermatitis. In the first stage, the images of the skin diseases are subject to different pre-processing techniques followed by segmentation and extraction of features. The second stage involves the use of machine learning (ML) algorithms to detect diseases based on extracted texture features. After comparing all the methods, in a one to one combination, the maximum accuracy acquired is 93.37 percent using the combination of NL-SVM and IQA.**

***Keywords*— Skin Disease; Pre-processing; Segmentation; GLCM; IQA; Statistical parameters; Jaccard Index; Dice Coefficient; AUC-ROC; K-fold Cross Validation;**

## I. INTRODUCTION

A work on segmentation of the skin diseases (Seborrheic Dermatitis, Melanoma, Impetigo and Diabetic Foot Ulcer) using Digital Image Processing Technology has already been done by the authors who are writing this paper. The skin is the largest organ of the human body. It is composed of epidermis, dermis, and subcutaneous tissues, containing blood vessels, lymphatic vessels, nerves, and muscles, which can perspire, perceive the external temperature, and protect the body. So, a greater problem can be led by any harm to the skin. Many different skin disease detection processes have been proposed by many authors but our proposed system is built to detect the four diseases namely: Seborrheic Dermatitis, Diabetic Foot Ulcer, Impetigo, and Melanoma. The authors have characterized the four diseases and described the harmful effects of the diseases in their first research. Furthermore, the pros and cons of the three segmentation methods (Markercontrolled watershed algorithm, Otsu thresholding and K-means clustering algorithm) have been discussed by them [1].

The GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity (a.k.a. image texture) at the pixel of interest. Image quality can refer to the level of accuracy in which different imaging systems capture, process, store, compress, transmit and display the signals that form an image. (IQA) have been researched and developed over the last several decades. Today, IQA research has emerged as an active sub-discipline of image processing. Image quality can refer to the level of accuracy in which different imaging systems capture, process, store, compress, transmit and display the signals that form an image. Image quality assessment is part of the quality of experience measures.

Support Vector Machines have one built-in "layer" that helps with having an interpretation of the data - the kernel. There is also an implied "layer" in image feature construction. The k-Nearest Neighbor classifier is by far the most simple machine learning/image classification algorithm, it simply classifies unknown data points by finding the most common class among the k-closest.

In the first stage of this paper, four different skin disease images that occur in humans have been pre-processed, segmented and extracted the features. The three segmentation methods have been compared using the Jaccard Index and Dice Coefficient. Then two feature extraction methods have been compared using different parameters. After that, the results have been evaluated to find out which method is good for segmentation and feature extraction for which particular disease. In the second stage, three different classification methods based on extracted features have been applied to detect the four diseases and compared to find out the best classifier.

All the systems developed till now have worked on segmenting similar types of diseases (similarity-based on

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color, shape, etc.) but not on different diseases. There are few works on Impetigo and Diabetic Foot Ulcer. Marker Controlled Watershed and the K-Means algorithm have been used by few authors. There is no comparison of segmentation methods to clarify which segmentation method gives the best result. Boundary regioning, differentiating pixel distribution, waterbag, or pus validation in Diabetic Foot Ulcer has not done by any author. SVM and KNN comparison has also not been done. These things motivated us to implement the proposed system.

The rest of this paper is organized as follows. Section 2 describes the past works on skin disease detection; Section 3 gives a description of the dataset used in the research and the different tasks. Section 4 describes the evaluation metrics. Section 5 describes the result analysis. Section 6 gives an analysis of the whole system and finally section 7 concludes this paper with a few comments and suggestions for future research.

## II. LITERATURE REVIEW

The past works on pre-processing and segmentation methods have been discussed by the authors in their first research [1]. International Semantic Intelligence Conference (ISIC) has used Area Under Curve-Receiver Operating Characteristic (AUC-ROC) curve, 3-Fold Cross Validation, Specificity and Sensitivity to investigate the performance of the challenge sets [2]. Li-sheng Wei et al. have used the Support Vector Machine to classify the diseases [3]. Lakshay Bajaj et al. have converted the resulting diseased region into a feature vector and fed into Artificial Neural Network [4]. Pravin S. Ambad et al. have proposed a work where different statistical parameters have been studied amongst them- Entropy, Texture Index, Correlation Factor have been chosen to find out probability of diseases[5]. The integration of K-Means Clustering with the Marker-Controlled Watershed algorithm has given better segmentation. The current practices used by dermatologists include Biopsy, Scrapings, Diascopy, Patch Testing, and Prick Test which are invasive methods of detection [6] [7] [8] [9].

Some research article shows that Multilayer Perceptron Classifier (MLP) can be used to classify the lesion as being Benign or Malignant. M. Kumar and R. Kumar has researched on the performance of KNN algorithms, which have been applied to infected skin images of humans in terms of different research topics: skin image detection, image processing, and image recognition and image classification [10] [11][12].

For disease classification, the system has resorted to Feedforward Backpropagation Artificial Neural Networks[13][14]. Some researchers have focused on different Deep Neural Network algorithms to increase the accuracy [15] [16] [17] [18].

Another proposed method has been applied to measure the wound 'size' and control the illness evolution[19]. R.S. Ground et al. have extracted GLCM features, first-order histogram, dermoscopic and color features. After that SVM & C4.5 have been used to classify the diseases. Nine different diseases have been classified based on color features by some authors [20] [21] [22].

## III. DATASET DESCRIPTION AND TASKS

The paper consists of four tasks: Image pre-processing, Segmentation, Feature extraction & Classification task shown in figure 1. The first three tasks combine the computer vision stage and the last task constitutes the machine learning stage. 4170 images of Melanoma, Impetigo, Seborrheic Dermatitis, and Diabetic Foot Ulcer have been collected from different medical websites (Dermnet, ISIC, Derm101, DermIS, Dermofit, Dan-derm, PH2 and many more). Then, the images have been resized and splitted into two parts, 67% of the total images have been used for training, and 33% for testing. Another 1250 set of images have been used for validation.

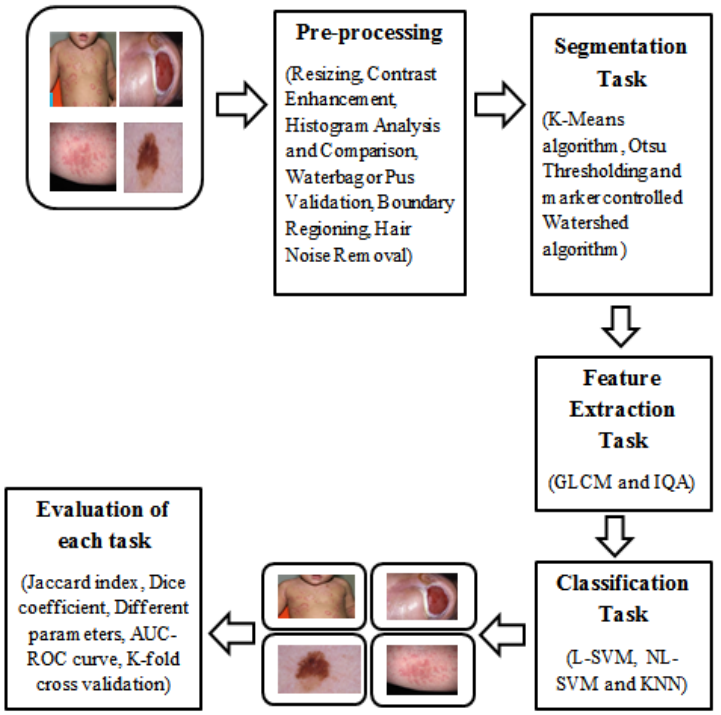



Fig 1: The flowchart of the system.

### *A. Part 1: Preprocessing Task*

In this task, different preprocessing techniques have been applied. First of all, Contrast enhancement has been done for all the images in the dataset. Figure 2 and 3 show the original image and result of contrast enhancement on Diabetic Foot Ulcer disease respectively. Histogram analysis of the images has been implemented for differentiating the pixel distribution between the four different diseases. Figure 4 shows the histogram of image in figure 2. Our system works to detect a disease called Diabetic Foot Ulcer and there is waterbag or pus inside the hole of the Foot Ulcer. To validate this waterbag or pus inside the hole, Sobel operator has been applied shown in figure 5. Some Melanoma images have hair as noises. The Dull Razor algorithm has been used to remove the hairs of the Melanoma images shown in figure

6(b). Another preprocessing technique which has been applied is boundary regioning. The output of boundary regioning has highlighted the infected area of the images. In figure 6(c), the result of boundary regioning has been shown on the image of figure 6 (a).

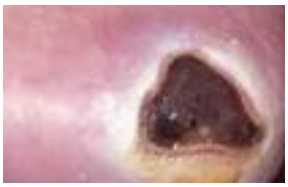


Fig 2: Diabetic Foot Ulcer image.

Fig 3: Contrast enhanced image.

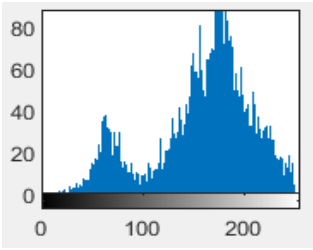



Fig 4: Histogram.

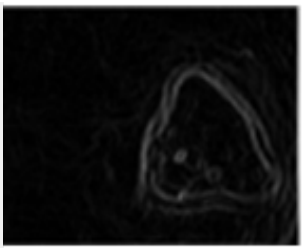


Fig 5: Waterbag or pus validation.

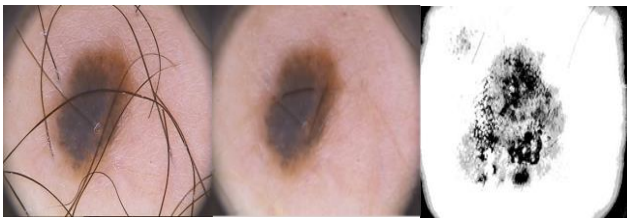


Fig 6: (a) Melanoma image, (b) After noise removal, (c) Boundary regioning.

### B. Part 2: Segmentation Task

For segmenting the infected part of the diseases, three segmentation methods namely Marker-controlled Watershed algorithm, K-means Clustering Algorithm and Otsu Thresholding have been used shown in figure 7. The segmentation task begins by converting the input image into gray image. In Marker-controlled Watershed algorithm, the background and foreground markers are detected and in this way, the infected area has been segmented. With the use of 5 clusters, the K-means Clustering algorithm has been implemented. The properly segmented infected parts of the images have been found in the second cluster for Melanoma and Seborrheic Dermatitis disease. But for Impetigo and Diabetic Foot Ulcer, the third cluster has given the correctly segmented images. Otsu thresholding process has also been applied which returns a single intensity threshold that separates pixels into two classes, foreground-background and has properly segmented the infected and non-infected regions of the four diseases.

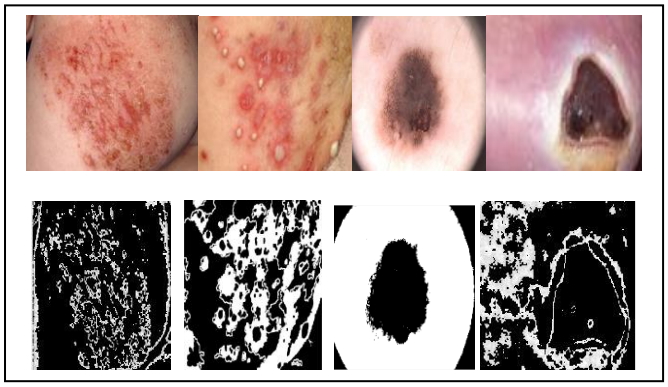


Fig 7: Applying three different segmentation methods. Top: Original images. Bottom: Segmented images. Left to Right: Seborrheic Dermatitis using K-means, Impetigo using Marker Controlled Watershed, Diabetic Foot Ulcer using K-means & Melanoma using Otsu Thresholding.

### C. Part 3: Feature Extraction Task

In this task, the features from the segmented images have been extracted for further classification task. Two feature extraction methods, GLCM and IQA have been used. 13 features have been extracted using GLCM. The features are Entropy, Mean, Standard Deviation (STD), Variance, Kurtosis, Skewness, Contrast, Correlation, Energy, Homogeneity, Root Mean Square (RMS), Smoothness and Inverse Difference Movement (IDM). Features extracted from IQA method are 11 in number and they are namely: Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Global Contrast Factor (GCF), Average Difference (AD), Mean Squared Error (MSE), Structural Similarity Index Measurement (SSIM), Structural Content (SC), Normalized Cross-Correlation (NK), Maximum Difference (MD), Normalized Absolute Error (NAE) and Laplacian Mean Square Error (LMSE).

TABLE I. RESULTS SHOWING 11 IQA FEATURES OF SEBORRHEIC DERMATITIS, MELANOMA, IMPETIGO AND DIABETIC FOOT ULCER.

| Features | SNR | PSNR | GCF | MSE | SSIM | AD | SC | NK | MD | LMSE | NAE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Seborrheic Dermatitis** | 7.7995 – 16.9199 | 0.3246 – 12.2931 | 100.1169 – 253.8947 | 3835 – 60342 | -0.0107 – 0.1940 | 23.4164 – 243.2955 | 1.1663 – 47.3010 | 00272 – 0.5743 | 177 -- 255 | 5.1008 – 2485.9013 | 0.6144 – 0.9719 |
| **Melanoma** | 6.9314 – 47.4049 | 0.9818 – 7.6268 | 0.0000 – 20.5260 | 1123 -- 5186 | 0.00014 – 0.0626 | 93.4047 – 224.3155 | 1932 – Inf | 0.0000 – 0.0071 | 147 -- 255 | 0.9688 – 1.0116 | 0.9929 – 1.0000 |
| **Impetigo** | 6.9315 – 19.0729 | 0.0749 – 9.2200 | 2.3464 – 20.0706 | 7781 – 63913 | 0.00016 – 0.2116 | 55.6530 – 254.0727 | 13061 -- 2607299 | 0.0004 – 0.0064 | 176 – 255 | 0.9951 – 1.0774 | 0.9919 – 0.9999 |
| **Diabetic Foot Ulcer** | 7.8804 – 21.3883 | 0.1692 – 12.8362 | 59.2893 – 251.8883 | 3384 – 62541 | -0.0042 – 0.3489 | 18.9771 – 249.5004 | 1.5246 – 119.0645 | 0.0094 – 0.5367 | 187 – 255 | 8.9367 – 2639.4030 | 0.6056 – 0.9884 |

TABLE II. RESULTS SHOWING 13 GLCM FEATURES OF SEBORRHEIC DERMATITIS, MELANOMA, IMPETIGO AND DIABETIC FOOT ULCER.

| Features | Seborrheic Dermatitis | Melanoma | Impetigo | Diabetic Foot Ulcer |
|---|---|---|---|---|
| **Entropy** | 0.2566 -- 0.9774 | 0.0000 -- 1.0000 | 0.1346 – 1.000 | 0.1299 – 0.9997 |
| **Mean** | 7.6752 - 58.5921 | 0.0000 – 0.9756 | 0.0188 – 0.8239 | 3.1057 – 63.8691 |
| **STD** | 36.2240 – 81.6327 | 0.0000 – 0.5000 | 0.1358 – 0.5000 | 23.0113 – 78.9336 |
| **Variance** | 131.2181 – 666.3901 | 0.0000 – 0.2500 | 0.0184 – 0.2500 | 53.0442 – 623.0508 |
| **Kurtosis** | 1.1575 – 21.6189 | 1.0000 – 3274.8000 | 1.0000 – 51.2572 | 1.1233 - 55.0776 |
| **Skewness** | 0.3726 – 4.5293 | -6.1611 – 57.2171 | -1.7008 – 7.0892 | 0.1486 – 7.3294 |
| **Contrast** | 1.1230 – 11.9750 | 0.0000 – 7.6489 | 0.1047 – 4.1108 | 0.3066 – 9.5062 |
| **Correlation** | 0.3703 – 0.9282 | 0.4498 – 0.9842 | 0.8268 – 0.9863 | 0.5263 – 0.9229 |
| **Energy** | 0.3732 - 0.8924 | 0.3852 – 1.0000 | 0.4245 – 0.9610 | 0.3963 – 0.9585 |
| **Homoge -neity** | 0.7862 - 0.9799 | 0.8634 – 1.0000 | 0.9266 – 0.9981 | 0.8302 – 0.9945 |
| **RMS** | 37.0280 – 98.0948 | 0.0000 – 0.9877 | 0.1371 – 0.9077 | 23.2396 – 100.2873 |
| **Smoothness** | 0.9999 -- 1.0000 | 0.0000 – 1.0000 | 0.9992 – 1.0000 | 0.9995 -- 1.0000 |
| **IDM** | 0.1019 -- 174.9642 | 0.0000 – 1.0766 | 0.0467 – 2.0767 | 0.1110 -- 178.5663 |

### *D. Part 4: Classification Task*

After all the features have been extracted, the system moves forward to classification process. The three-classifier used are L-SVM, NL-SVM, and KNN. Same train and test data have been used to train these three models. KNN has performed best with the parameter k = 13 for GLCM and k = 3 for IQA.

## IV. EVALUATION METRICS

Evaluation metrics are used to measure the quality of the statistical or machine learning model. For evaluating the performance of different kinds of machine learning classification techniques, there are many types of statistical parameters like accuracy, precision, recall, F1 score, etc. In this research, the three classification methods (L-SVM, NL-SVM and KNN) have been compared by measuring accuracy, error, specificity, sensitivity, precision, recall, f1-score, true positive rate, false positive rate, true negative rate and false negative rate. Alongside the area under curve (AUC) measurement from the receiver operating characteristic (ROC) curve and 10 fold cross validation have been done.

The comparison of segmented methods has also been done. Dice Coefficient and the Jaccard Index have been used to evaluate the performance of the segmentation methods.

## V. RESULTS

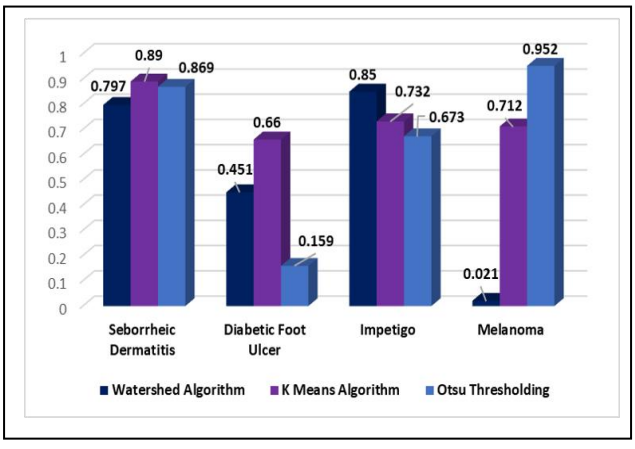
In this research, the skin disease detection system has been implemented in four different tasks. In the following, the results of each task are investigated with proper figures and data.

### *A. Segmentation Task*

In the segmentation process, three methods have been used as mentioned earlier. The comparison among the three methods has been done by Jaccard Index and Dice Coefficient shown in figure 8. The Jaccard similarity index (sometimes called the Jaccard similarity coefficient) and Dice Coefficient measure the similarity of two sets of data. The segmentation method with the more value of Jaccard and Dice can more accurately segment the infected part of the diseases.

From figure 8, it is seen from the graphs that K-means clustering algorithm has given the highest Jaccard index value of 0.492 and Dice coefficient value of 0.66 for Diabetic Foot ulcer. K-means also has given the maximum Jaccard index and Dice coefficient values for Seborrheic Dermatitis and the values are 0.802 & 0.89 respectively. Marker controlled watershed algorithm has given the best Jaccard and Dice values for Impetigo disease which are 0.739 & 0.85. The Melanoma disease has been properly segmented by Otsu thresholding and that's why the Jaccard index value of Melanoma using Otsu thresholding is higher than the other three diseases. The Jaccard value using Otsu thresholding is 0.909. Dice coefficient value is also higher than the other three methods which is 0.952.

So, it can be concluded that for Seborrheic Dermatitis and Diabetic Foot Ulcer, K means clustering algorithm gives better segmentation output, for segmenting the infected part of Impetigo disease, Marker controlled watershed algorithm is a good choice and for Melanoma disease, Otsu thresholding is mostly preferable for segmentation purpose.



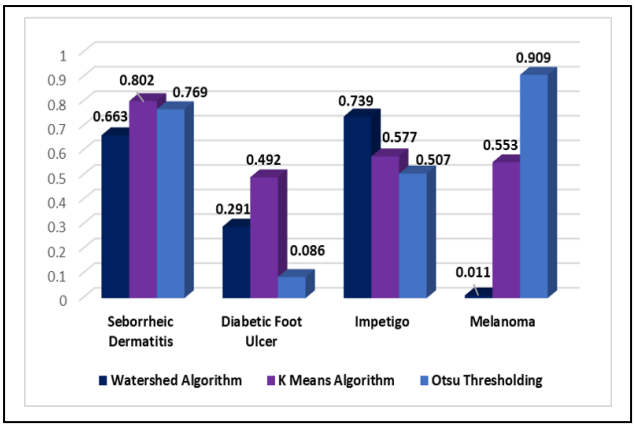




Fig 8: Bar chart of Jaccard Index and Dice Co-efficient values from three segmentation methods for each disease.

### *B. Feature Extraction & Disease Classification Task*

1. Different statistical parameters: The disease classification task received 1376 images as test data and 2794 images as train data. Performance characteristics of the L-SVM, NL-SVM & KNN with both GLCM and IQA are shown in Table III. From the table, the statistical parameter results can be analyzed. There are 11 parameters namely True Positive Rate, False Positive Rate, True Negative Rate, False Negative Rate, Accuracy, Error, Sensitivity, Specificity, Precision, Recall, and F1 Score. The comparison of these parametric results can be done in two approaches. First of all, if the comparison is done based on the feature extraction method, it has been seen that the GLCM method has given the best value of these 11 parameters for Linear SVM and KNN classification. The value of the parameters for Linear SVM classification using GLCM are 88.86%, 11.14%,0.850, 0.950, 0.852, 0.850, 0.851, 86.63%, 5.01%, 95%, 15% respectively. KNN classifier has also an accuracy rate of 86.01% by using GLCM features. The TPR, FPR, TNR, FNR values of KNN classifier are 83.67%, 5.44%, 94.56%, 16.33% respectively. All values are pretty much better than the values given by IQA extracted features. So, for Linear SVM and KNN classification, using GLCM features will yield better classification. On the other hand, Non-Linear SVM classification's parametric values are higher with IQA extracted features. By looking at the table it is observed that the Accuracy, Error, F1 Score, Specificity, Precision, TPR, FNR values are 93.37%, 6.63%, 0.895, 0.965, 0.896, 89.46%, 10.54% respectively using IQA extracted features. But those values are comparatively low if GLCM extracted features are used. Thus, it can be said that for Non-Linear SVM classification, IQA feature extraction method is a good choice.

TABLE III. VALUES OF DIFFERENT EVALUATION METRICS FOR THREE CLASSIFIERS (L-SVM, NL-SVM, KNN) WITH TWO FEATURE EXTRACTION METHODS (GLCM & IQA).

| Statistical Parameters | Classification Methods | Feature Extraction Methods | |
|---|---|---|---|
| | | GLCM | IQA |
| Accuracy (%) | L-SVM | 88.86 | 35.76 |
| | NL-SVM | 90.61 | 93.37 |
| | KNN | 86.01 | 80.34 |
| Error (%) | L-SVM | 11.14 | 64.24 |
| | NL-SVM | 9.39 | 6.63 |
| | KNN | 13.99 | 19.66 |
| Sensitivity | L-SVM | 0.850 | 0.213 |
| | NL-SVM | 0.866 | 0.895 |
| | KNN | 0.837 | 0.730 |
| Specificity | L-SVM | 0.950 | 0.738 |
| | NL-SVM | 0.955 | 0.965 |
| | KNN | 0.946 | 0.910 |
| Precision | L-SVM | 0.852 | 0.219 |
| | NL-SVM | 0.868 | 0.896 |
| | KNN | 0.837 | 0.729 |
| Recall | L-SVM | 0.850 | 0.213 |
| | NL-SVM | 0.866 | 0.895 |
| | KNN | 0.837 | 0.729 |
| F1 Score | L-SVM | 0.851 | 0.131 |
| | NL-SVM | 0.866 | 0.895 |
| | KNN | 0.837 | 0.729 |
| True Positive Rate (TPR) (%) | L-SVM | 84.99 | 21.33 |
| | NL-SVM | 86.63 | 89.46 |
| | KNN | 83.67 | 72.93 |
| False Positive Rate (FPR) (%) | L-SVM | 5.01 | 26.22 |
| | NL-SVM | 4.46 | 3.51 |
| | KNN | 5.44 | 9.02 |
| True Negative Rate (TNR) (%) | L-SVM | 95 | 73.78 |
| | NL-SVM | 95.54 | 96.49 |
| | KNN | 94.56 | 90.98 |
| False Negative Rate (FNR) (%) | L-SVM | 15 | 78.67 |
| | NL-SVM | 13.37 | 10.54 |
| | KNN | 16.33 | 27.07 |

Again, from table III, the comparison can also be done based on classification methods. If either GLCM or IQA, one of the feature extraction methods are used and the three classification methods are compared then the performance of the classifier can be achieved. First of all, considering GLCM as feature extraction method, the classifiers are evaluated by its value of Accuracy, Precision, F1 Score, TPR, TNR, FPR and FNR, so the mentioned parameter values are respectively 88.86%, 0.852, 0.851, 84.99%, 5.01%, 95%, 15% for L-SVM classifier, 90.61%, 0.868, 0.866, 86.63%, 4.46%, 95.54%, 13.37% for NL-SVM classifier and 86.01%, 0.837, 0.837, 83.67%, 5.44%, 94.56%, 16.33% for KNN classifier. From the values, it has been seen that all parameter values are higher in NL-SVM classification and so it can be said that NL-SVM is the best classifier among the other two classifiers in case of detecting the four mentioned diseases namely Dermatitis, Melanoma, Impetigo & Diabetic Foot Ulcer. Now, if IQA is considered as feature extraction method and the same parameters are evaluated then it is observed that the NL-SVM classification method gives better results (Accuracy: 93.37%, error: 6.63%, sensitivity: 0.895, specificity: 0.965, precision: 0.896, recall: 0.895, f1 score: 0.895, TPR: 89.5%, FPR: 3.51%, TNR: 96.49% and FNR: 10.54%). Thus, after analyzing the data of the table, it can be concluded that the NL-SVM classifier is more accurate classifier than L-SVM and KNN for classifying skin diseases (Dermatitis, Melanoma, Impetigo & Foot Ulcer).

2. ROC-AUC Curve: An alternative approach to get a visual representation of classifier output is the ROC curve. The curve is plotted for each classifier in figure 9. It is used to evaluate the classifier by plotting the TPR (sensitivity) against FPR (1-specificity). The area under a receiver operating characteristic (ROC) curve, abbreviated as AUC, is a single scalar value that measures the overall performance of a binary classifier. Considering this distribution, using GLCM feature extraction method, NL-SVM classifier gave better performance for Dermatitis, KNN classifier for Diabetic Foot Ulcer & Impetigo and lastly L-SVM for Melanoma.

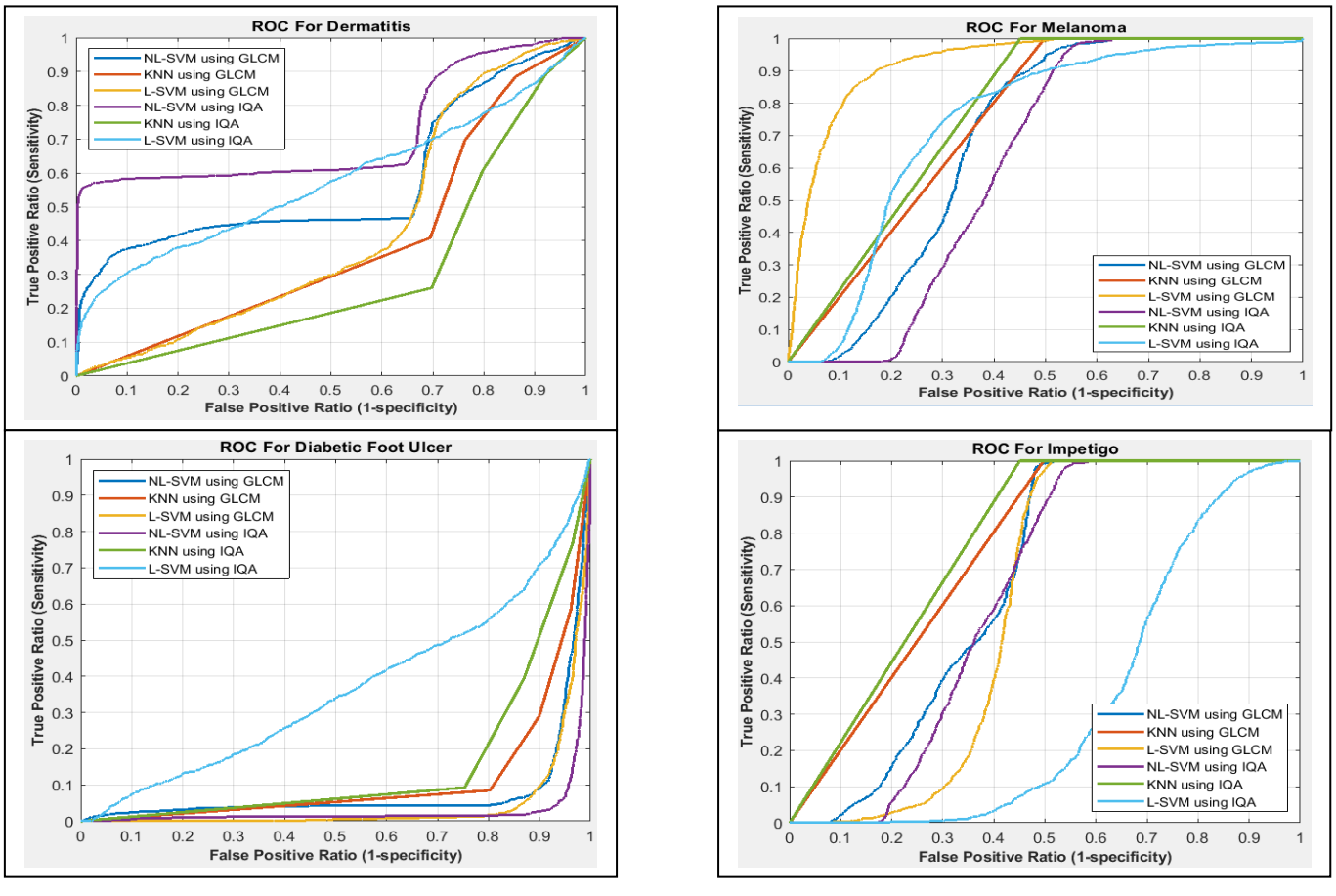



Fig 9: ROC Curves of the four diseases using GLCM & IQA.

3. K-fold Cross Validation: The K-fold Cross Validation is a procedure used to estimate the skill of the model on new data. That is, to use a limited sample in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the training of the model. In this paper, 10 folds have been used to cross validate a set of 1250 images.

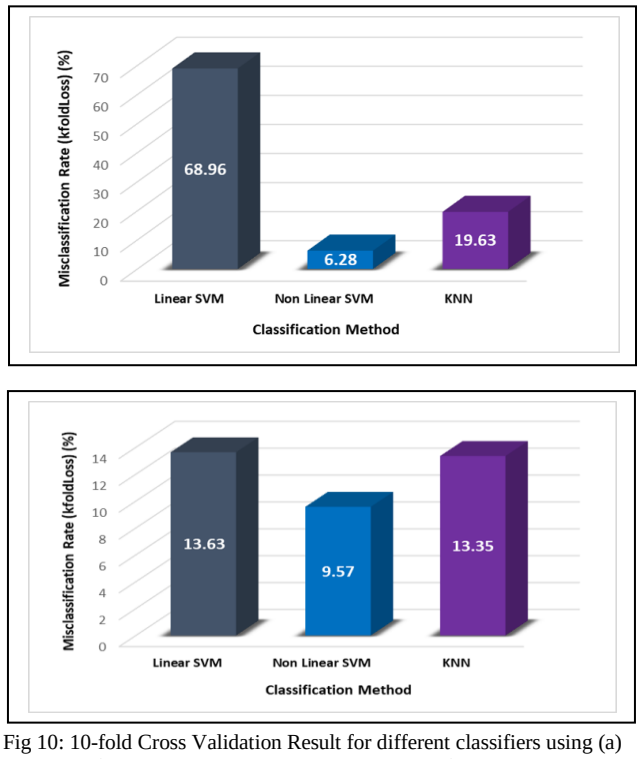



Fig 10: 10-fold Cross Validation Result for different classifiers using (a) IQA as feature extraction method, (b) GLCM as feature extraction method.

The figure 10(a) graph shows that misclassification rates of L-SVM, NL-SVM and KNN are 68.96%, 6.28% and 19.63% respectively. By analyzing the above graph, it is observed that the NL-SVM classifier has a lower classification rate than the other two methods. That means the NL-SVM classifier can classify more accurately than L-SVM and KNN classifiers when IQA method has been used for extracting features. Figure 10(b) graph shows that misclassification rates of L-SVM, NL-SVM and KNN are 13.63%, 9.57% and 13.35% respectively. So, the NL-SVM classifier has a lower classification rate than the other two methods which means it can classify more accurately than L-SVM and KNN classifiers when GLCM method has been used for extracting features.

## VI. DISCUSSION

The research was divided into 4 tasks: pre-processing, segmentation, feature extraction and classification. Different pre-processing techniques, three segmentation methods, two feature extraction methods and three classifiers have been used to detect four different diseases.

Analysis of segmentation results suggest that Marker controlled watershed is good for Impetigo disease, K means clustering algorithm is good for Seborrheic Dermatitis & Diabetic Foot Ulcer and Otsu Thresholding is good for Melanoma disease. So, when the infected part of the diseases has to be segmented those methods can be used to get more accurate results.

Analysis of feature extraction task gives us the idea that for better detection of the diseases, Linear SVM and KNN classification methods can be used with GLCM extracted features & Non-Linear SVM classification can be used with IQA extracted features. Analysis of classification task shows that the NL-SVM classifier is the best among the three classifiers and it classifies all the four diseases more accurately.

Deep Neural Network has not been used in this system because the accuracies obtained from the machine learning algorithms are good enough. All the systems developed till now have worked with one or two ML algorithms but in our system we have implemented and compared three different ML algorithms to pick the best one for a particular disease.

Limitations of this study include collecting the necessary data image of patients. It is one of the most challenging tasks in developing a machine learning application especially for evaluating skin disease detection. So, there were two choices either to collect the images manually from public hospitals, or individual patients or using online resources of the skin disease image database. For the manual collection of the data, two major problems were faced. The first one is that there is a lack of data collection in most of the local hospitals, the second problem is that if there are data available, those are hardly reachable because the data are considered private for the hospitals and require permissions from the authorities, so it was decided to use online resources. For the online resources option, there are a lot of resources available on various websites for skin disease images but there was not a direct way to download a whole image dataset at once, so every single image had to be downloaded individually. Moreover, the quality of the images has not been up to the mark for that a couple of pre-processing techniques had been applied, which is time consuming. Furthermore, the configuration of computers which are used to develop the system was not too high so accuracy from the classification methods was low. If images and computer with higher quality can be used then the accuracy can be increased to a satisfactory number.

## VII. CONCLUSION

As in this paper, different segmentation, feature extraction and classification methods have been compared and results have been analyzed, so this study can help to develop applications for the detection of mentioned four diseases more accurately and this can help patients to detect their diseases before going to doctor or having any medical help. Thus, they can take precautions which can make life safer. Our system can be improved by adding various skin tones of infected patients such as brown/dark skin tones in the dataset, increasing the training data with real time images from patients for training the model. These will make the system more robust and increase the accuracy.

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