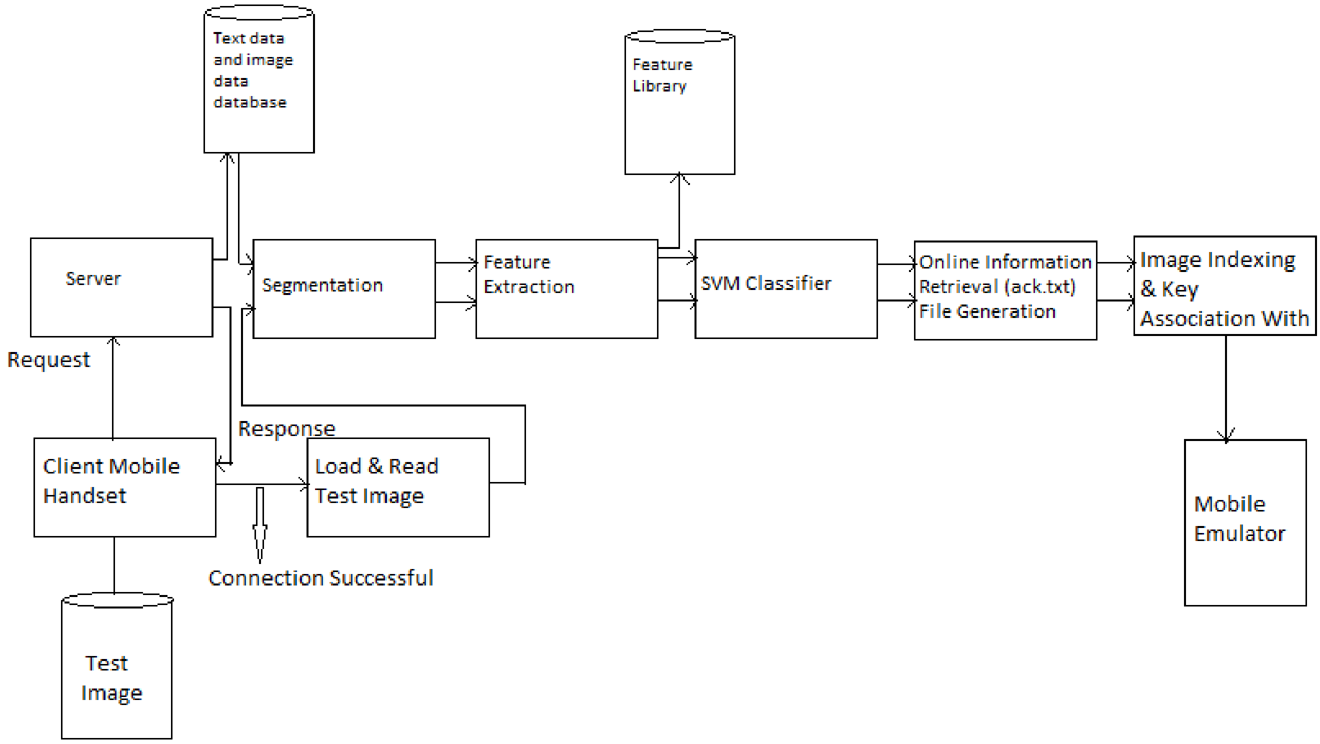

Figure 1: Proposed Architecture

The proposed architecture is as shown in the above diagram, where test image is sent from the client side i.e., mobile device by requesting the server for connection to be established between the client and the server. Once after the connection is setup between the client and the server through IP ADDRESS and the PORT NUMBER, the communication is possible between them. The client mobile handset does a request to the server by sending a test image, the server responses, thus making a connection successful for reading and loading the test image. The server consist a database with the images and associated medical information literature which is used for verifying the stages and concerned diagnosis for the test image that is burnt wound injury image of the patient. Then image processing is done in order to identify the similarity of the injury in the test image by applying the transformation steps in order to fetch the features which are further tested with the existing features stored at the database once after the features are extracted. The ack.txt file is generated through online information retrieval, then the image indexing and the key association is done which is further provided to the client side mobile as the results. The medical information obtained as the results at the client mobile device is further used as the diagnosis steps for the burnt wound injury of the patient.

4.1 Data Collection

The dataset of medical images are collected from the www.pbase.com/510picker/burn i.e., burn photos photo gallery by Matthew Rodenbeck who says the burn photos are good example of the healing progression of burns. The sample of images of each class is as shown in the Figure 2.

Figure 2: Sample images of each stage

4.2 Segmentation

Once after the images are collected, images are segmented using shearlet transformation. Shearlet Transform is a multiscale directional transform with a greater ability to localize distributed discontinuities such as edges. Unlike traditional wavelets, shearlet transforms are theoretically optimal and has the ability to fully capture directional and other geometrical features. Shearlets are highly effective at detecting both location and orientation of edges and also helps in detection of corners and junctions.

4.3 Feature Extraction

The features that are to be extracted are texture and color. Discrete Wavelet Transform is used to extract texture features and Hue, Saturation and Value model is used for extracting the color features.

4.3.1 Discrete Wavelet Transformations

Suppose $x=\{x_{ij}$, i=1,2,…,M and j=1,2,…,N$\}$ is an image of M x N pixels, which is corrupted by independent and identically distributed (i.i.d) zero mean, white Gaussian noise n_{ij} with standard deviation σ_n. The noise signal can be denoted as $n_{ij} \sim N(0,\sigma^2)$. This noise may corrupt the signal in a transmission channel. The observed, noise contaminated, image is $y=\{y_{ij}$, i=1,2,…,M and j=1,2,…,N}. Therefore, the noised image can be expressed as:

$$y_{ij} = x_{ij} + n_{ij} \qquad \text{----(1)}$$

The object of a de-noising process is to estimate image x from the noised image y, so that the Mean Square Error (MSE) to be minimum. Let W and W denote the two dimensional DWT and its inverse respectively. Then, the original signal, its noised version and the noise have a matrix form in the transform domain that includes the sub band coefficients.

$$X = W x \,,\ Y = W y \,,\ V = W n \qquad \text{----(2)}$$

The Figure 3 shows the two level DWT of a 2-D signal, which consists of the sub bands LL(low frequency or approximation coefficients), HL(horizontal details), LH(vertical details), HH (diagonal details) and the first level details HL, LH, HH. Therefore equation 1, in the spatial domain, becomes in the transform domain as follows:

$$Y = X + V$$

where X, Y and V are the transform domains of the original image, its noised version and the noise respectively. The orthogonal property of the transform insures that the noise in the transform domain is also of Gaussian nature. The de-noising algorithms, which are based on thresholding, suggest that each coefficient of every detail sub band is compared to a threshold level and is either retained or killed if its magnitude is greater or less respectively. The approximation coefficients are not submitted in this process, since on one hand they carry the most important information about the image and on the other hand the noise mostly affects the high frequency sub bands.

The main assets of the wavelet transform is the ability to compact most of the signal's energy into a few transformation coefficients, which is called energy compaction and to capture and represent effectively low frequency components (such as image backgrounds) as well as high frequency transients (such as image edges).And also the ability of a progressive transmission, which facilitates the reception of an image at different qualities.

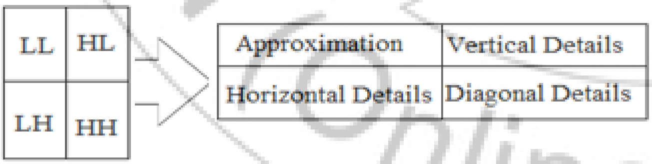

Figure 3: Values of the image after applying DWT

4.3.2 Hue, Saturation and Value

The hue (H) of a color refers to which pure color it resembles. The saturation (S) of a color describes how white the color is. The value (V) of a color, also called its lightness, describes how dark the color is. The mean and standard deviation of images are calculated. The global mean value of an image is the average intensity of all the pixels in the image. Let A be NxM image. Then its global mean

$$m=\sum_{k=0}^{L-1} r_k p(r_k)$$

Where r_k is the kth intensity value, $p(r_k)$ is the probability of occurrence the intensity .Variance (Dispersion) is the second moment of intensity about its mean m.Variance (Dispersion) is the second moment of intensity about its mean

$$\sigma^2 = \mu_2(r) = \sum_{k=0}^{L-1} (r_k - m)^2\, p(r_k)$$

where m is the mean, r_k is the kth intensity value, $p(r_k)$ is the probability of occurrence the intensity r_k. Standard Deviation is the square root of the variance

$$\sigma=\sqrt{\sigma^2}=\sqrt{\sum_{k=0}^{L-1}(r_k-m)^2 p(r_k)}=\sqrt{\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left(A(i,j)-m\right)^2}{NM}}$$

The importance of mean and standard deviation is that the mean is a measure of average intensity and closer is mean to the middle of the dynamic range, the higher contrast should be expected whereas the standard deviation is a measure of contrast in an image and the larger is standard deviation, the higher is contrast.

4.4 Classification

Once the segmentation and feature extraction process is done the classification is the next step to be performed. Thus the detection of the different stages of burnt wound is obtained by applying the SVM multiclass classifiers to the set of medical images.

4.4.1Support Vector Machine

In machine learning, Support Vector Machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

5. Results and Discussion

The following are results obtained of our work. The Figure 4(a) represents the menu showing the button options for creating database, SVM training, selecting a query, retrieving the result and the exit. The Figure 4(b) represents the original image. The Figure 4(c) represents the grayscale image of the original image. The Figure 4(d) represents the DWT converted image of the query image. The Figure 4(e) represents HSV image of the original image. The Figure 4(f) shows the shearlet coefficients of the original image. The Figure 4(g) displays the screen of the client side mobile device showing the options for providing port number, IP address, browsing the medical image from the mobile device, and the send button option to send the image to the server. The Figure 4(h) displays the screen after browsing the image and ready to send the image to the server. The Figure 4(i) shows the screen with the message that the image has been sent successfully to the server. The Figure 4(j) shows the client mobile device screen with the textual medical information retrieved which is associated with the respective stage that the burnt wound injury query image belongs to from the server.

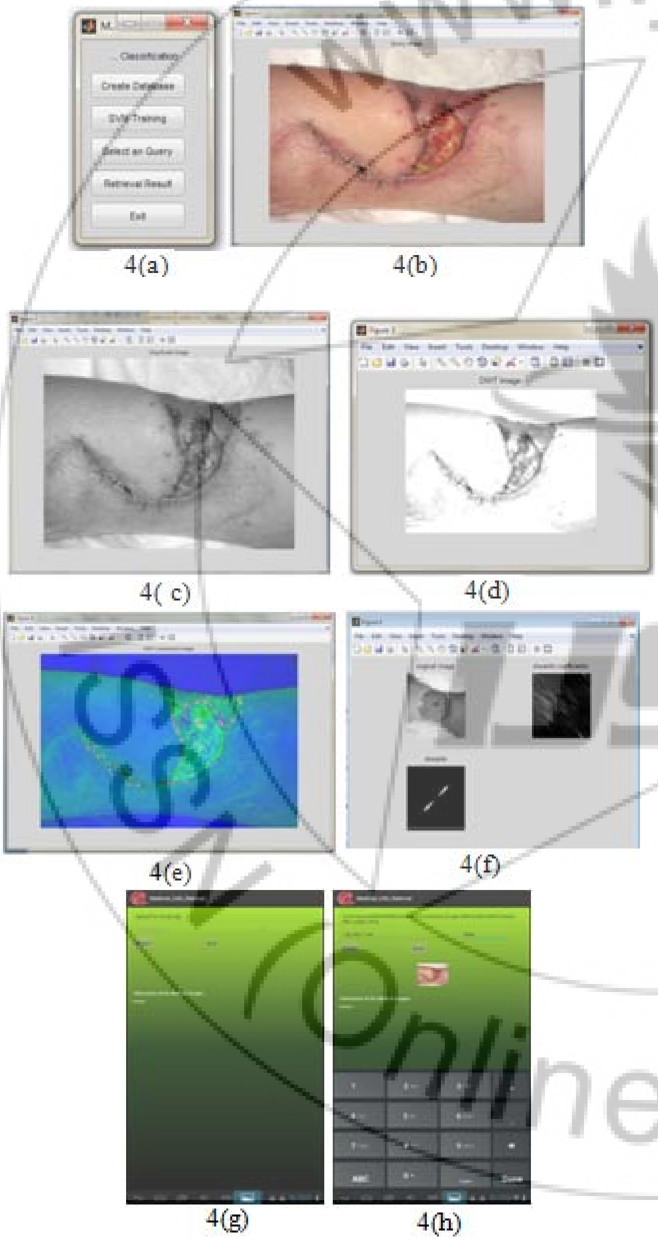

Figure 4: The above figures represent the results obtained

The Figure 5 displays the graph of performance accuracy of our work. The X-axis represents the five different stages of the burnt wound injury of our dataset and the Y-axis represents the retrieval accuracy. The different retrieval accuracies are associated with each stage. The stage 1 has the retrieval accuracy of 40% because the images that belongs to this has more shining and jelly blood like appearance so it's difficult to extract the features. Stage 3 has the accuracy of 50% where in it is difficult to distinguish the wounded region from the normal skin region. The Stage 2 has the accuracy of 65% where the wounded part is observed by the boundary of stitches and the specific features are extracted. Stage 4 has 75% of accuracy because the images have the injury which is deeper and unable to extract the relevant features from those images. Finally, stage 5 has the images where in the burnt wound portion and the normal skin is clearly distinguishable and thus the features are extracted accurately hence having retrieval accuracy of 90%.

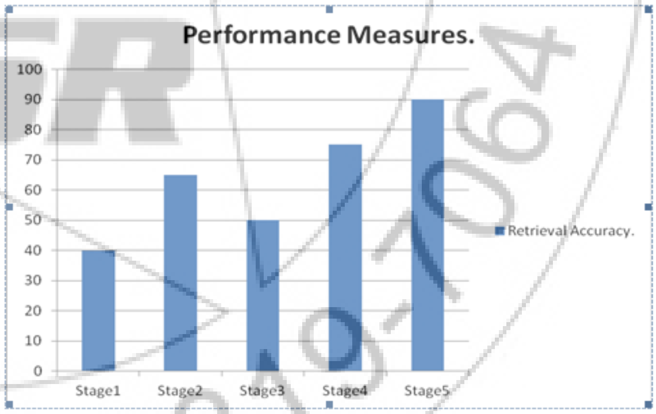

Figure 5: The plot representing the retrieval accuracies of each stage

6. Conclusion

Medical visual information retrieval on mobile devices is possible with the medical Information Retrieval application. The medical information retrieval engine is successfully adapted to the various constraints imposed by mobile devices. Enhanced ease of use of the interface and optimized screen space are achieved. The results are a web application that is visually similar to native applications, with good execution speed and optimized communication bandwidth. When the performance is measured it observed that each stage retrieval accuracy is different depending upon the images they contain. The graph previously shown represents the retrieval accuracy of each stage. The graph previously shown represents the retrieval accuracy of each stage. The stage 1 has the lowest retrieval accuracy of 40% because the images that belongs to this has more shining and jelly blood like appearance so its difficult to extract the features. Stage 5 has the images where in the burnt wound portion and the normal skin is clearly distinguishable and thus the features are extracted accurately hence having highest retrieval accuracy of 90%.

7. Future Scope

The use of the proposed mobile medical framework is also expected to enhance the current medical information systems to improve the quality of care and patient safety, increase clinician productivity, and reduce the risk of medical errors. It can be easily extended to many other medical applications such as clinical decision support, group diagnosis, virtual hospitals, and personalized predictive healthcare systems. Such systems would include mobile on-demand home healthcare services, implemented by means of wireless connectivity between medical experts, their patients, and hospital medical data, in a secure and reliable fashion.

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