# Medical Information Retrieval through Mobile Devices

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**Abstract:** ***The proposed work deals with the development of a methodology for the classification of different stages of burnt images of human using image processing techniques. The burnt images of human at the leg part with different deepness of injuries are considered as dataset. The dataset includes the five classes representing phases of injuries, 10 images in each phase amounting to total of 50 images. The work mainly focuses on segmenting region into two parts, namely homogenous regions (background) and burnt part. For extracting the burnt region shearlet transform segmentation technique is applied. The shearlet transform is a multistate directional transform with a greater ability to localize distributed discontinuities such as edge region of wounded part. The shearlet transform found to be very efficient for segregating the injured part which further helped for the classification of burn stages. Further, features are extracted for wound region with texture and color features. The wavelet transform is adopted for texture extraction and color moments namely mean and standard deviation are extracted. The features are trained with the Support Vector Machine (SVM) classifier. The classification results are reported. The work helps for the dermatologist for disease diagnosis.Thus, the proposed system has the potential to facilitate information access and increase quality of patient care in clinical environment by making essential information available to the appropriate person at the appropriate time.***

**Keywords:** Shearlet Transform, Wavelet Transform, Mean, Standard Deviation Support Vector Machine

## 1. Introduction

Dermatology is the branch of medical science that is concerned with diagnosis and treatment of skin based disorders. The vast spectrum of dermatological disorders varies geographically and also seasonally due to temperature, humidity and other environmental factors. Human skin is one of the most unpredictable and difficult terrains to automatically synthesize and analyze due to its complexity of jaggedness, tone, presence of hair and other mitigating features. Even though there have been several researches conducted to detect and model human skin using Computer Vision techniques, very few have concentrated on the medical paradigm of the problem. Expert diagnostic systems that deal with dermatological disorders are hard to find in the scholarly area of Intelligent and Expert Systems. Therefore, our system addresses such complexities of the school of dermatology of medical science. Even though a substantial amount of work has undergone in the amalgamation of medicine and computer science, little research has been conducted that connects computer vision and dermatology. Techniques are used for segmentation of dermatoscopic or burnt images. They focused on segmenting only the burnt portion of the leg from the regular skin surfaces. Since mobiles are used everywhere by everybody. The online access of medical information through mobile technology is found to be very less. Hence, the usage of mobile technology along with image information is very much necessary.

Mobile technology is the technology used for cellular communication. Mobile code division multiple access (CDMA) technology has evolved rapidly over the past few years. Since the start of this millennium, a standard mobile device has gone from being no more than a simple two-way pager to being a mobile phone, GPS navigation device, an embedded web browser and instant messaging client, and a handheld game console. Many experts argue that the future of computer technology rests in mobile computing with wireless networking. Mobile computing by way of tablet computers is becoming more popular.

The next generations of smart phones are going to be context-aware, taking advantage of the growing availability of embedded physical sensors and data exchange abilities. One of the main features applying to this is that the phones will start keeping track of your personal data, but adapt to anticipate the information you will need based on your intentions. There will be all-new applications coming out with the new phones, one of which is an X-Ray device that reveals information about any location at which you point your phone. One thing companies are developing software to take advantage of more accurate location-sensing data. How they described it was as wanting to make the phone a virtual mouse able to click the real world. An example of this is where you can point the phone's camera while having the live feed open and it will show text with the building and saving the location of the building for use in the future.

When designing your mobile communication, be aware that the viewing screen on mobile devices are much smaller than the viewing screen on a desktop or laptop computer. Because of this, text that is readable on a desktop can become illegible when viewed on a mobile device. Instead of creating text heavy presentations, try to replace words with images that will display favorably on a mobile device.

## 2. Literature Survey

Mobile access to peer–reviewed medical information based on textual search and content–based visual image retrieval is possible Visual and textual retrieval engines with state of the art performance were integrated. Results obtained show a good usability of the software. Future use in clinical environments has the potential of increasing quality of patient care through bedside access to the medical literature in context[1].An intelligent information retrieval system that uses clustering and multidocument summarization techniques to present a large set of results in a restricted size environment is implemented. The software client running on PDA only transmits to the server the necessary data for the query and waits for the results in order to be displayed on the PDA screen[2].A mobile patient monitoring system, which integrates current personal digital assistant (PDA) technology and wireless local area network (WLAN) technology is presented. At the patient's location, a wireless PDA-based monitor is used to acquire continuously the patient's vital signs, including heart rate, three-lead electrocardiography, and SpO2. A mobile patient monitoring system was designed, developed, and tested [10].

Home care services are growing up in the past years. With the social trends, the senior population has been increasing in the last years. The difficulties of transport in the big cities and the scarcity of hospital streambeds turn the home care an attractive solution. However, its routines can be switched by telemedicine [9].Patient clinical data are distributed and often fragmented in heterogeneous systems, and therefore the need for information integration is a key to reliable patient care. a mobile clinical information system (MobileMed), which integrates the distributed and fragmented patient data across heterogeneous sources and makes them accessible through mobile devices[3].An analysis of usability of mobile prescription reference systems in medical practice, and presents implementation of mobilePDR(Physician's Desk Reference). The successful deployment and operational life of the mobilePDR system with a modest amount of maintenance effort proved that the initial concept and realization were appropriate [8].Information management in a hospital setting requires significant collaboration, mobility, and data integration. The care of one patient can involve many devices, such as x-ray machines and blood-pressure monitors; artifacts other than devices, such as patient records; and a variety of staff, such as doctors, laboratory personnel, and social workers [7].

Context-aware computing is a central concept in ubiquitous computing and many suggestions for context-aware technologies and applications have been proposed. . In our qualitative research, clinicians report on the benefit of having access to view context information on colleagues and operating rooms. The display of location, status, and current activity significantly helped them improve their coordination of work [4].Hospitals are complex work environments where information and people are distributed, thus requiring considerable coordination and communication among the professionals that work in such settings. Electronic medical records are an important step toward providing adequate access to clinical information [6].

Hospital information systems (HISs) that provide access to electronic patient records are a step in the direction of providing accurate and timely information to hospital staff in support of adequate decision-making. With adequate support to estimate the context of work, context-aware systems can deliver information that is relevant to the user's location, identity, and/or role [5].

## 3. Problem Definition

Work at hospital settings requires considerable mobility and coordination due to the complexity of the tasks performed the intensity of the information exchange, and the fact that information and resources are distributed throughout the premises. A hospital's staff might be distributed in space (i.e., different location within the settings) or time (i.e., working different shifts) and their information needs are highly dependent on their location and other contextual conditions such as their role or time of the day. Doctors may not be present at the patient's location all the time. The condition of the patient burnt wound injury is captured through camera and sent to the server in order to access the associated medical information regarding the treatment i.e., diagnosis information of the injury. The server consists of the database with stored information regarding the injuries. Thus by obtaining the information the individual can treat the patient even in the absence of the doctor in order to cure the burnt wound injury.

## 4. Proposed Methodology

The Figure 1 shows the block diagram of working process of proposed methodology. It includes the following modules, namely: Data Collection, Segmentation, Feature Extraction, and Classification.

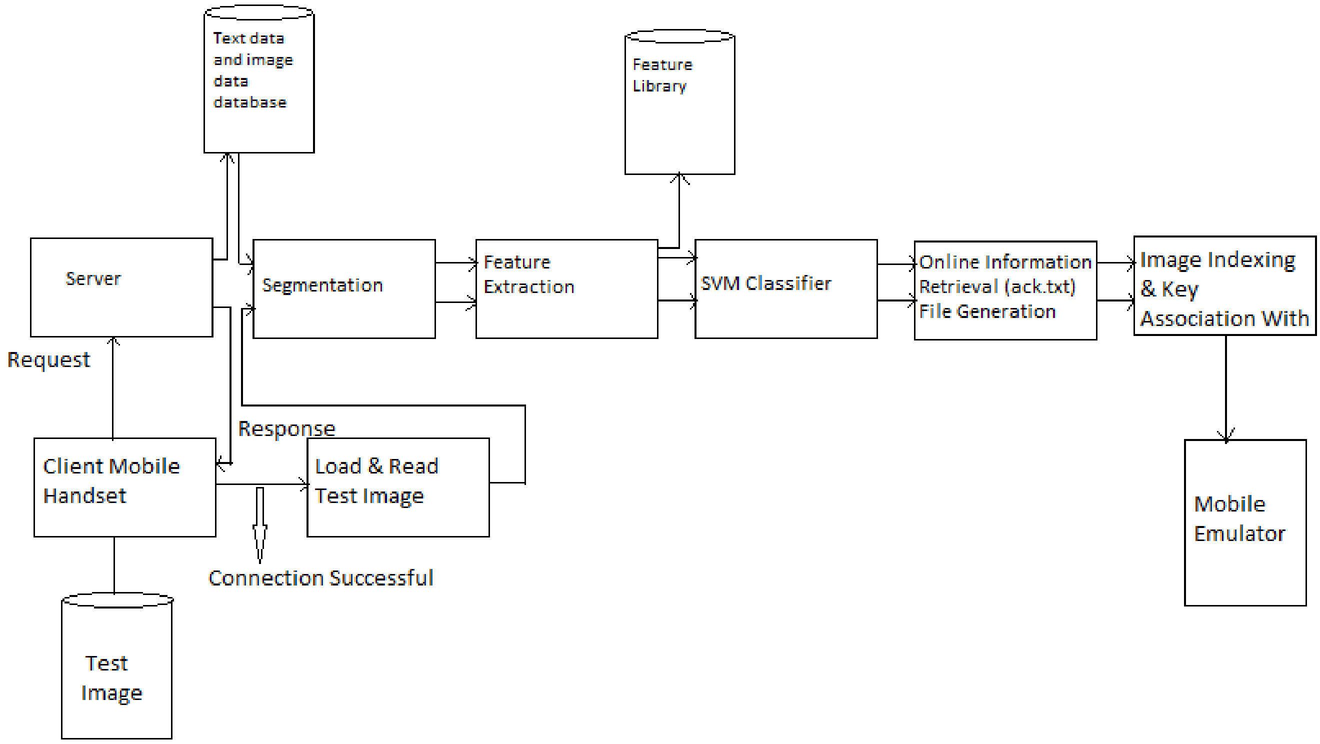


**Figure 1:** Proposed Architecture

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 $\sigma_n$. 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.

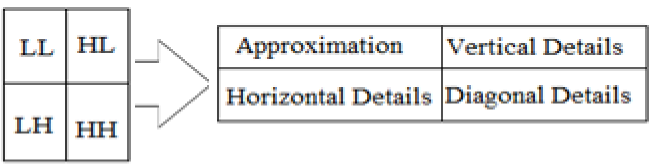


**Figure 3:** Values of the image after applying DWT

#### 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 $k$th 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 $k$th 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.

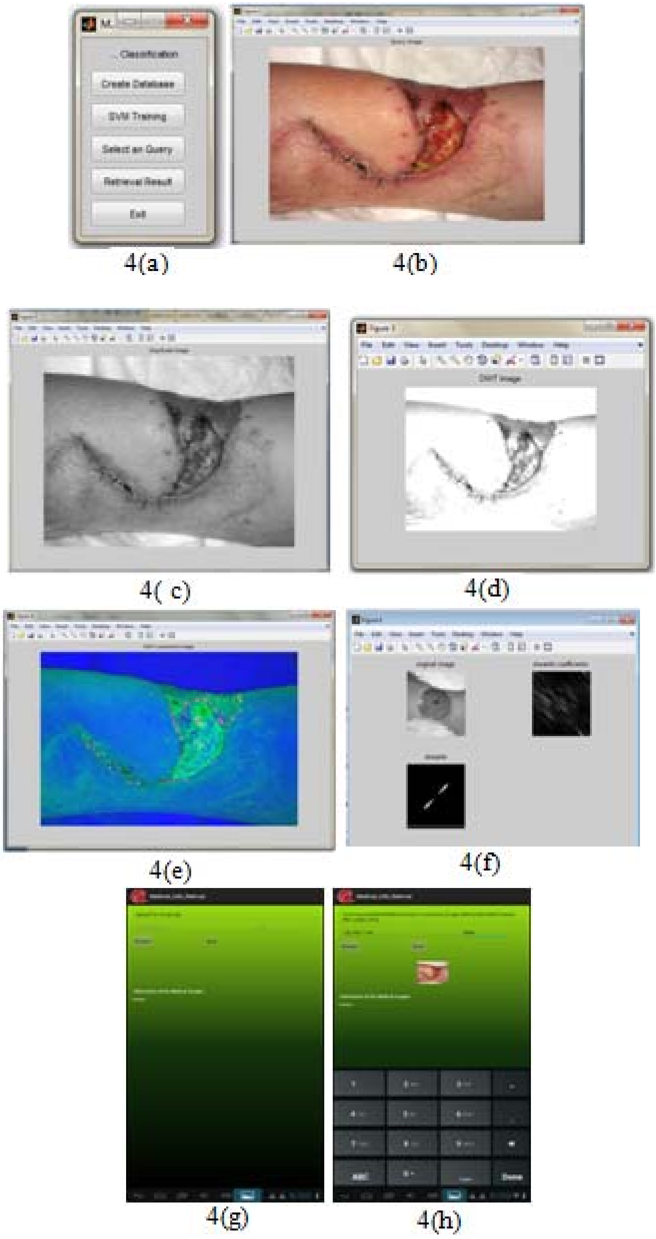



**Figure 4:** The above figures represent the results obtained

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%.

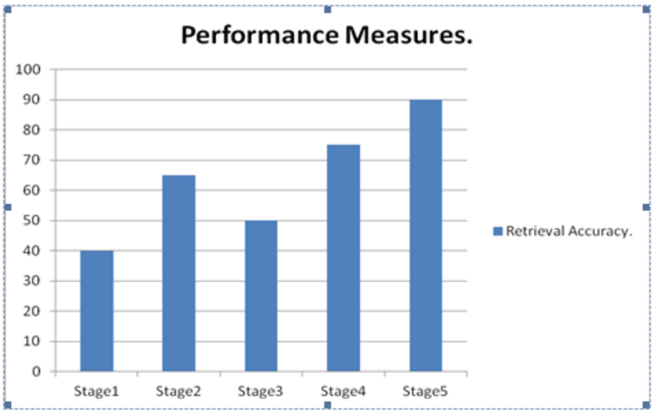


**Figure 5:** The plot representing the retrieval accuracies of each stage

## 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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## Author Profile

**Ashwini Tadkal** received the B.E degree in 2012 and pursuing M.tech(2012-2014) in Computer Science and Engineering from Poojya Doddappa Appa College of Engineering, Gulbarga, Karnataka, India. Image processing and information retrieval are the fields of interest.

**Dr. Suvarna Nandyal** is presently working as Professor in Department of Computer Science and Engineering, Poojya Doddappa Appa College of Engg, Gulbarga, Karnataka, India. She received her BE degree in Computer Science & Engineering from Gulbarga University Gulbarga in 1993, M Tech degree in Computer Science & engineering from VTU Belgaum in 2003 and Ph.D. degree in Computer Science & Engg from Jawaharlal Technological University, Hyderabad, and Andrapradesh India in 2013. She has teaching experience of 20 Years. She has extensive research interests in Image processing, Video Processing, Speech Recognition, Cloud Computing and information retrieval. She is member of ISTE and IETE. She has published number of research papers in International/National journals and conferences. She is involved in various academic activities such as curriculum development and professional society activities. She has guided post graduate students and two PhD scholars are working under her guidance.