Diagnosis of Burn Images using Template Matching, k-Nearest Neighbor and Artificial Neural Network

Malini Suvarna *maliniatria@gmail.com*
Research Scholar,
Dept. of E&C,
Atria Institute of Technology, Bangalore

Dr. Sivakumar *sivabs2000@yahoo.co.uk*
Head Dept. of TC,
Dr. Ambedkar Institute of Technology, Bangalore

Dr. Kamal Kumar *drkamalkumar25@yahoo.co.in*
Plastic Surgeon,
Rajarajeshwari Medical College, Bangalore

Dr. U C Niranjan *ucniranjan@yahoo.com*
Director of Research and Training,
Manipal Dot Net, Manipal

ABSTRACT

The aim of this research is to develop an automated method of determining the severity of skin burn wounds. Towards achieving this aim, a database of skin burn images has been created by collecting images from hospitals, doctors and the Internet. The initial pre-processing involves contrast enhancement in lab color space by taking luminance component. Various pattern analysis or pattern classifier techniques viz. Template Matching (TM), k Nearest Neighbor Classifier (kNN) and Artificial Neural Network (ANN) have been applied on skin burn images and a performance comparison of the three techniques has been made. The help of dermatologists and plastic surgeons has been taken to label the images with skin burn grades and are used to train the classifiers. The algorithms are optimized on pre-labeled images, by fine-tuning the classifier parameters. During the course of research, of the three classifier methods used for classification of burn images it has been observed that the ANN technique reflected the best results. This has been inferred based on the comparative studies of the three methods. In the ANN method the classification of the image of burns has been found to be the nearest to the actual burns. The efficiency of the analysis and classification of the ANN technique has been of the order of 95% for Grade-1 burns, 97.5% for Grade-2 burns and 95% for Grade-3 burns. As compared to 55%, 72.5% and 70% for Grade1, Grade2, and Grade 3 burns respectively for the TM Method and 67.5%, 82.5% and 75% for kNN method. It is therefore felt that the ANN technique could be applied to analyze and classify the severity of burns. This burn analysis technique could be safely used in remote location where specialists' services are not readily available. The local doctors could use the analyzer and classify the grade of the burn with a good degree of accuracy and certainty. They could start preliminary treatment accordingly, prior to specialists' services. This would definitely go a long way in mitigating the pain and sufferings of the patients.

Keywords: ANN, TM, kNN.

1. INTRODUCTION

Medical Imaging is a boon given by science and technology to humanity. While on the one hand medical diagnostics has advanced in leaps and bounds, on the other hand advancement in image processing, pattern recognition and machine intelligence techniques has intensified medical imaging. With these advancements it is now possible to make diagnostics in a non-invasive manner. An easy and correct diagnostic facilitates appropriate treatment earlier and thereby enhance chances of full recovery, while reducing the pain and suffering of patients. Modern techniques are also cost effective.

For a successful evolution of a burn injury it is essential to initiate the correct first treatment [1]. To choose an adequate one, it is necessary to know the depth of the burn, and a correct visual assessment of burn depth highly relies on specialized dermatological expertise. As the cost of maintaining a burn unit is very high, it would be desirable to have an automatic system to give a first assessment in all the local medical centers, where there is a lack of specialists [2], [3]. Burn injury is one of the major accidents and life threatening causes in the modern world. Handling and management of burn victims is done in special wards in hospitals by specially trained personnel. Skin is the largest organ of our body and it gets damaged predominantly during burn accidents. Skin accounts for 15% of the total weight of an adult human being. The basic functions of the skin are protection, sensation, and temperature regulation, synthesis of vitamin D. The principal components of the human skin are epidermis and dermis. Epidermis is the outer thinner part of the skin, while the dermis is the inner thick layer of connective tissue made of elastic fibers. The World Health Organization demands that, at least, there must be one bed in a Burn unit for every 500000 inhabitants. So normally, one Burn Unit covers a large geographic extension [4]. If a burn patient appears in a medical center without Burn unit, a telephone communication is established between the local medical center and the closest hospital with Burn Unit, where the non-expert doctor describes subjectively the color, texture and status considered important for burn characterization. The result in many cases is the application of an incorrect first treatment (very important on the other hand for a correct evolution of the wound), or unnecessary displacements of the patient involving high sanitary cost and psychological trauma for the patient and family.

When a person meets with a burn accident the skin layers get affected. Doctors determine the degree of burns by examining which layer and organs are affected and suggest treatment. The work proposed here focuses on automating this process. A digital camera is used to capture the burn images of the patient and the software developed would analyze the image. Using the outcome of this research, severity of the injury can be estimated, the degree of burns can be calculated and the depth of the injured tissue can be quantified.

Skin Burns Images are collected from open source database of images and also from the burn ward of some hospitals. The images are digital and color. In order to assess the progress of healing of wound, a series of images of wound subjected to medication and palliative care are acquired. A data base of such images with substantial number was constructed to validate the outcome of this research. The general and clinical details of the subjects such as gender, age, ethnicity, treatment history, cause and type of burn and experts opinion is collected for each image.

General image processing and enhancement algorithms applicable to wound characterization is applied in this work on medical skin burn images. Usual flow of computer based processing begins with contrast enhancement, feature extraction from the red, green and blue components such as variance, mean, hue, saturation, intensity, texture, shape, and area. As there are no invasive techniques to assess the nature of the wound, computerized techniques are proposed as a cost effective solution.

The proposed automatic wound analyzer would be useful at remote locations where medical experts are not available. During accidents as the patient gets admitted to the hospital or while being transported in ambulance, the medical personnel attending the patient can send burn images immediately through online camera to the specialist. When the images reach the specialist, he can decide the line of treatment. He can diagnose whether surgical intervention is required or the patient can be treated by palliative methods. This will aid the patient recovery, it will also serve as a good teaching and research tool for students of health care. This would also serve as an aid in the follow up and further pathology for the burns. The proposed system is built and optimized such that it would use little computational resources, power and would computes faster.

The proposed algorithm software is first developed on the Matlab with the help of Image processing toolbox to enhance and pre-process the raw images [5, 6]. Proposed System is shown in Figure 1.1.

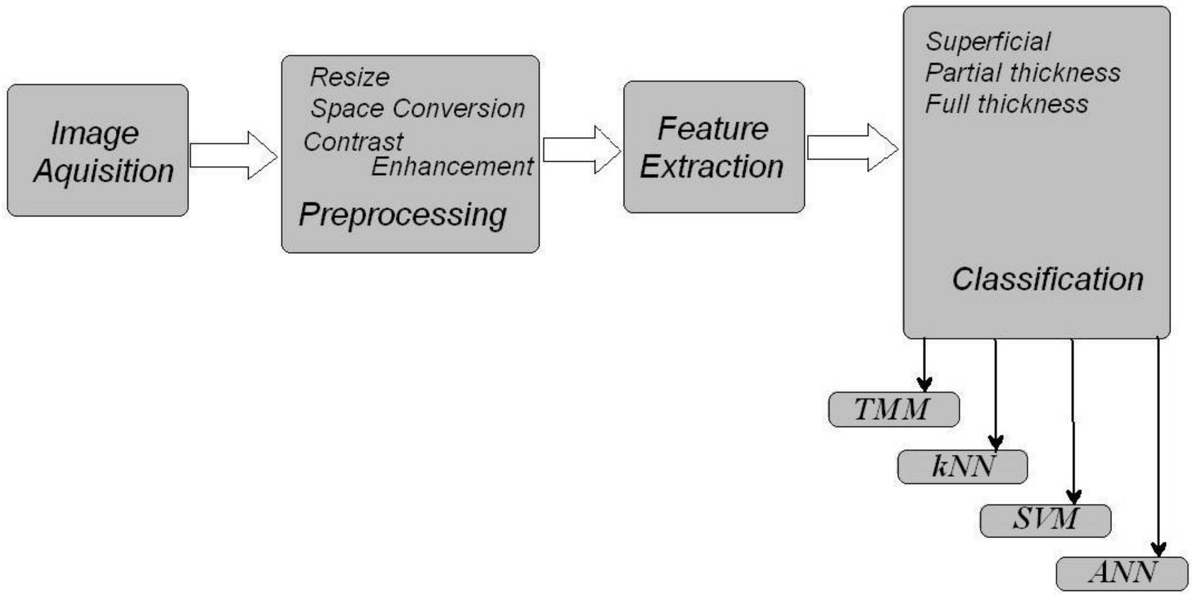


FIGURE 1.1: Proposed Burn Image Diagnosis System.

1.1 Literature Survey

Ongoing experimental research on skin burn images is very less. Thus, contribution to this field of research is not much. Contributions have been done particularly by the researchers from Spain, belonging to Biomedical Engineering Group of Seville University. Though the work is of significant importance, very little research has been done.

The following is the list of researchers who have contributed to this field of activity:

Gary L. Hansel et.al. [7]: This researcher developed clinical evolution of burn injuries using an optical reflectance technique.

Gary L. Hansel et.al.[9]: have proposed a method for the diagnosis of burns and pressure ulcers in the early stage using computerized image processing. These authors have diagnosed burns and pressure ulcers in the early stages, using color image processing, and have developed a method for quantifying the histological readings and have applied these readings to model wound formation. By making the color analysis and taking the hue factor of the wound, mild, moderate and severe types of the wounds are detected, using the time of injury as known variable.

Jean Phillipe.et.al. [16]: Have developed an algorithm to detect cancerous tissues from an image of microscopic section. Based on the shape and size of the cell, using mathematical morphology the tissues are classified into malignant or benign. Depending on the mathematical value obtained for each cell, the tissues are categorized into four groups.

Martin.et.al. [8]: They designed a new clinical instrument for evaluating burn depth. The imaging burn depth indicator produces a true color and a false color image of burn. The false color image consists of upto four colors, each of which indicates a distinct range of probability that the area of burn so colored will heal with in 21 days.

J K Bennet et.al. [12]: They have evaluated the burn depth by the use of radio active isotope.

Serrano et.al. [2]: The research scholars belonging to the Biomedical Engineering Group of Seville University have made a study to find the effectiveness of telemedicine for plastic surgery applications. They have considered burn images for tele-diagnosis by capturing the burn image in a digital camera and compressing it for transmission through a communication media

Begona Acha et.al. [11]: have proposed a method classifying burn into their depth, based on features extracted from color and texture characteristic of burn images. A fuzzy art map neural network and SVM classifier used for this work.

Begona Acha et.al. [10]: have proposed a method to separate burn skin from a normal skin in burn color images and to classify the according to the depth of the burn. In the classification part we take advantages of color information by clustering, with the vector quantization algorithm. The color centroids of small squares taken from the burnt segmented part of the images in the ($V_1 V_2$plane in two possible groups where $V_1 V_2$are the two chrominance component of the CIE lab representation.

Begona Acha) et.al. [4]: Here the author classifies burn into different grades (of depth) based on feature extracted from the color and texture characteristic of burn images addressed. A Fuzzy-ATMAP neural network and non-liner SVM with the different type of kernels have been compared.

2. CLASSIFICATION OF BURN INJURIES

Classification of the burn injury in this work, mainly depends on the color of the wound. Injury to the top layer of skin epidermis is called superficial burn. Injury to the second layer of skin dermis is called a partial thickness or dermal injury. An injury that extends down to the third layer subcutaneous tissue which includes fat is called a full thickness injury.

2.1 Superficial (Grade 1) Burn

In superficial burn epidermis layer of the skin gets affected. Best example is sun burn heal with in 5 to 7 days. Superficial burn is as shown in Figure: 2.1

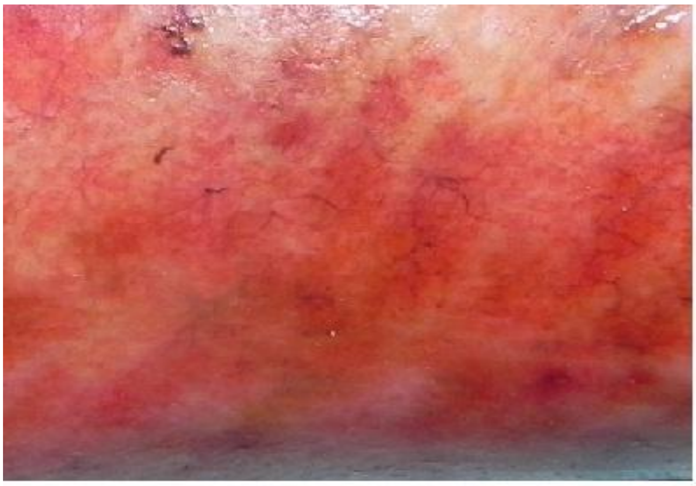


FIGURE 2.1: Superficial Dermal Burn.

2.2. Partial Thickness (Grade 2) Burn

In the Partial thickness burn dermis layer of the skin gets affected. Partial thickness burns usually leave scars. This will usually be treated with skin grafting Figure 2.2 shows a deep and large partial thickness burn.

FIGURE 2.2: Partial Thickness Burn.

2.3. Full Thickness (Grade 3) Burn

A full thickness burn destroys epidermis, dermis and subcutaneous layers of skin. Figure 2.3 shows a Full Thickness burn.

FIGURE 2.3: Full Thickness Burn.

3. DATABASE

Skin Burn Images of different grades are collected from hospital and Internet and scanned from biomedical books. Our database consists of a total of 120 images, 40 images from each grade of burn, as shown in Table 3.1. These images are labeled by the plastic surgeon. These images are used in the image classification. Once the algorithm is optimized on pre label images, it would be used to analyze non labeled images. Contrast enhancement and classification algorithm are applied to these images.

Type	No. of Images	Internet	Captured	Scanned from Books
Grade 1	40	8	27	5
Grade 2	40	7	28	5
Grade 3	40	4	32	4

Table 3.1: Database of Burn Images.

4. FEATURE EXTRACTION

Feature selection is very important while classifying the skin burn image into different grades. The selected features represent the characters of the images belonging to a particular category. Since the color of the skin burn images differs based on the depth of the wound, the color features of each image is extracted and used for the classifier training [1, 2].

In the research, initially the image is re-sized to 90*90 pixels, and then Red, Green and Blue (RGB) space is converted in to L*a*b* color space. Lab color space has 3 coordinates, one luminous and two chrominance V1 and V2. Luminous component is used for contrast enhancement. After contrast enhancement of the image, the V1 and V2 chrominance planes of the L*a*b* color space is selected for feature extraction. Further a 90*90 image is subdivided into 9*9 blocks and the features like mean and (2, 1)th coefficient of Discrete Cosine Transform (DCT) function is chosen to train classifiers. The two dimensional DCT equation is given below, where X(k1, k2) is the DCT and x(n1, n2) is the image

$$X(k_1 k_2) = \frac{4 \in_{k1} \in_{k2}}{N^2} \sum_{n_1=0}^{N_1-1} \sum_{n_2=0}^{N_2-1} x(n_1, n_2) cos\left(\frac{\pi(2n_1+1)k_1}{2N_1}\right) cos\left(\frac{\pi(2n_2+1)k_2}{2N_2}\right)$$

$$where \begin{cases} \in_k = \frac{1}{\sqrt{2}} for k = 0 \\ 1 otherwise \end{cases}$$

$$k = 0,1,2, \dots \dots, N$$

5. TEMPLATE MATCHING METHOD

This is a very simple and straight forward method of classification. Images of various classes of burns are first classified and systematically stored as reference templates. The burn images are compared with the reference templates to classify the sample burn images. Where the sample images match the burn image well, the error is would be the least. The figure 5.1given below illustrates the comparison of the sample images with a template. This type of comparison does not involve much computation. It is restricted to the number of samples to be compared and the number of templates available in the bank, proportionate to which the duration of time taken to compare and throw up a result would vary. Another limitation of the method is that when exact matches are not found the probability of mis-prediction increases. In this method the computational time increases as the number of sample increases [13].

FIGURE 5.1: Template Matching Method.

6. K-NEAREST NEIGHBOR CLASSIFIER

The possibility of an exact match between reference images and sample image not being found in the template method is addressed in this method. In this classification method a group of 'k' images from the reference images is selected which are the nearest match to the sample image. A label is assigned to the sample images band on the nearest 'k' image matching. The possibility of classification error where the image lies on the border of two classes is also overcome by this method where the labeling is based on average of 'k' images and not one reference image.

The steps involved in kNN classifies algorithm are:

1. A bank of labeled objects (burn images) is created. This bank serves as reference images for comparison. It is also called a "Training Set 'D'".
2. A distance or similarity metric that can be used to compute the closeness of sample objects is set up.
3. A value 'k' is generated which indicates the number of 'nearest' or 'closest' classes to the sample objects (images). The value 'k' varies depending on the intensity of the burn which is reflected in the image.
4. The 'k' nearest objects are used to determine the class of the target object or burn.

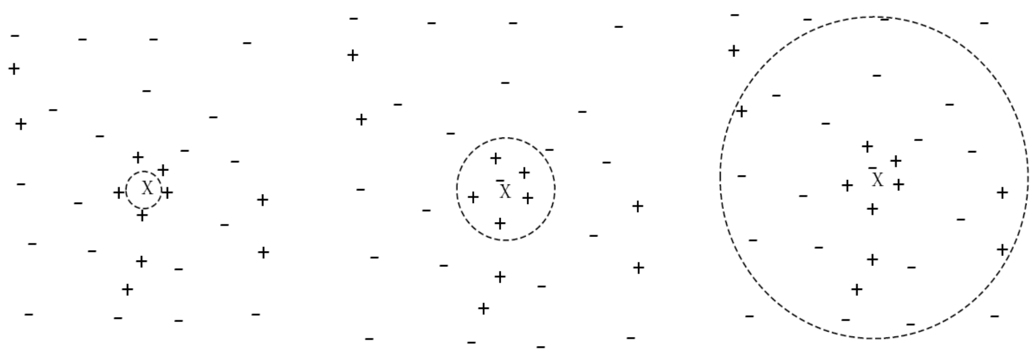
Consider a burn target object which needs to be classified. A set of images 'z' of the target object is compared with a training set of D images already set up. The algorithm compares nearness or closeness of the 'z' images with the set of D and computes k images which can be considered to be the nearest neighbors of the 'z' images of the target object. The value of 'k' images is generated by selecting images of 'D' based on their frequency in nearness to the 'z'.

The algorithm has a storage complexity of O(n), where n is the number of training objects or images Since the Euclidean distance of every test image needs to be computed with reference to the test objects the time complexity is also O(n). Since classification models viz. a decision tree or separating hyper plane is not constructed there is no time lost for this activity as in most other classification methods. While other classification methods are costly proportionate to the model building stages, kNN classification method is different and at the same time comparatively inexpensive since classification steps are constant 'O'.

Considering a data matrix *mxn where n reflects row vectors and data matrix of Y represented by mxn, the euclidean distance between the vector* x_s and y_t *is defined as:*

$$d^2_{st} = (x_s - y_t)(x_s - y_t)'$$

Selection of *k* value is very important in kNN classifier, this is explained in the Figure 6.1.



(a) Neighborhood too small.

(b) Neighborhood just right.

(c) Neighborhood too large.

FIGURE 6.1: Choosing k value in kNN.

Basic kNN Algorithm

Input : the set of objects taken for training ‘D’ or reference. Test object is ‘Z’ which is a vector of attribute values and set of classes used to label the objects L

Output: is reflected by *Cz*€*L*, the class of ‘z’ .

for each object Y€D

do

|Compute d(z, y), the distance between z and y;

end

7. ARTIFICIAL NEURAL NETWORK

Neural Networks are large networks of simple processing elements or nodes which process information dynamically in response to external inputs [14]. The nodes are simplified models of neurons. Artificial Neural Network (ANN) or Neural Network is a mathematical model inspired by biological neural networks. This network of inter connected artificial neurons process information using a connectionist approach to computation. During the learning phase, in most cases, a neural network is an adaptive system that changes structure. Neural networks are used to model between inputs and outputs or to find patterns in data.

The interconnections between the neurons in the different layers of each system is refered to by the word network in the term ‘artificial neural network’. The input neurons of the first layer send data via synapses to the third layer of output neurons. More complex system have more number of layers. The synapses store parameters called “weights” that operate on data in calculations.

An ANN is typically defined by 3 parameters:

1. The inter connection pattern between different layer of neurons
2. The learning process for updating the weights of inter connection
3. The activation function that converts neuron weighted input to output activation.

ANN's ability to be used as an arbitrary function approximation mechanism that 'learns' from observed data is probably the greatest advantage of ANN. It is however essential to use them for more complex and relatively good understanding of underlying theory.

1. Model Choice: Depends on data representation and application. A very complex model tends to lead to problem with regard to learning.

2. Learning algorithm: Many trade-offs exists between learning algorithms. With correct parameters for training on a fixed dataset almost any algorithm will work well. However significant amount of experimentation is required for selecting and tuning an algorithm for training on unseen data.

3. Robustness: ANNs can be made robust by choosing the correct model, appropriate cost function and proper learning algorithm.

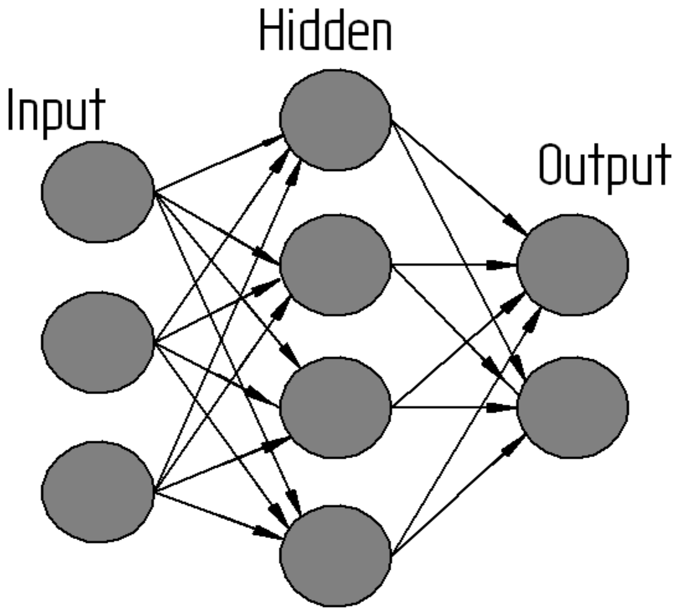


FIGURE 7.1: Architecture of Artificial Neural Network (ANN).

7.2 Training Using Back Propagation Algorithm

Back propagation learning emerged as the most significant result in the field of artificial neural network (15). Back Propagation Network (BPN) is a multilayered, fully connected feed forward network and uses supervised mode of learning. After an input pattern has been applied to the first layer of network units, it is propagated to each layer and an output is generated. This output is compared with desired output (target) and an error signal computed for each output unit. The error signal is transmitted backward from the output layer to each node in the hidden layer. This process repeats, layer by layer until each node in the network has received an error signal the describe its relative contribution to the total error. Based on the error signal received, connection weights are then updated by each unit to cause the network to converge towards a stage that allows all the training patterns to be encoded.

The back propagation network chosen in the work has two hidden layer one output layer and one in put layer. The network parameters chosen are:

- Learning Rate = 0.05
- Number of Hidden Layer = 2

- Number of Neuron in the 1st Hidden Layer = 10
- Number of Neuron in the 2nd Hidden Layer = 10
- Number of Neuron in the Input Layer = 2
- Number of Neuron in the Output Layer = 3

We have used following function \s for training ANN

- Transfer Function: Log Sigmoid
-

It takes around 1500 iterations to convergence. However the number of iterations change whenever a new ANN with new architecture is chosen.

7.3 Implementation Using BPA

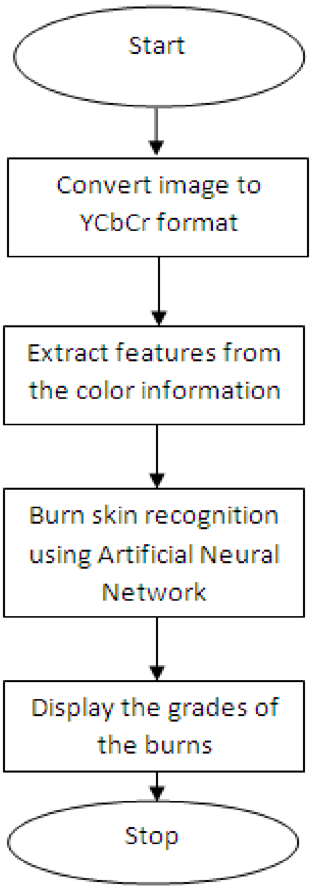


FIGURE 7.3: Flow Chart for Training ANN With Burn Images Using BPA .

8. RESULTS

8.1 Template Matching Method

This is the simple method of classification, a new test vector containing mean and DCT values of sample image is matched with the previously stored templates belonging to different grades. Depending on the closeness of the match, test sample is categorized. Testing of 120 images, with 40 images from each category is done and tabulated in Table 8.1. Twenty images from each category are used for training and remaining 20 for testing with cross validation.

Types of Image	No. of Images	Correctly Classified	Misclassified as			Efficiency as in %
			Grade 1	Grade 2	Grade 3	
Grade 1	40	22		6	12	55
Grade 2	40	29	4		7	72.5
Grade 3	40	28	9	3		70

TABLE 8.1: Template Matching Method.

8.2 kNN Classifier

In this method, classification is based on nearest neighbor method. Depending on the value of the k specified, algorithm checks for the k nearest neighbors of training values, surrounding a test value. The closest neighbor determines the class of test value. In this work, multi class kNN classifier is used with k value as 3. Cross validation of training and testing vectors are done by using 3 fold technique by randomly selecting training and testing vectors, the results of the classifier is shown in Table 8.2

Types of Image	No. of Images	Correctly Classified	Misclassified as			Efficiency as in %
			Grade 1	Grade 2	Grade 3	
Grade 1	40	27		4	9	67.5
Grade 2	40	33	5		2	82.5
Grade 3	40	30	7	3		75

TABLE 8.2: kNN Classifier.

8.3 ANN Classifier

In this method of classification Back Propagation Algorithm is used to train the ANN. Best efficiency is obtained when the 1st hidden layer contains 10 neurons and 2nd hidden layer contains 10 neurons. It takes 800 iterations to converge, however number of iterations change whenever the network is trained with different number of layers and neurons. ANN Classifier has resulted with an efficiency of more than 90% as shown in table 8.3:

Type of Image	No. of Images	Classified as			Efficiency in %
		Grade1	Grade2	Grade3	
Grade1	40	38	2	0	95
Grade2	40	0	39	1	97.5
Grade3	40	0	1	38	95

TABLE 8.3: ANN Classifier.

9. CONCLUSION

In this paper classification of the burn is achieved based on the depth of burn which is extracted from the color characteristics of burn images. The performance efficiency of three classifiers have been compared. It is seen that the ANN method of analyzing the Skin Burn Image reflects the grade of the injury very close to that by a Clinician. The features considered for classification are Mean and DCT. These features can be computed easily without any complex algorithm and thus reduces classification time. Burn Images are fed into the system and the grade of the wound would be displayed on the screen after the classification algorithm processes the image. Algorithms proposed are simple and thus result can be computed very fast. Using Internet and mobile phone the work can be converted to a tele medicine project.

ACKNOWLEDGMENT

Authors are thankful to Sri Devraj Urs Medical Center for providing the burn wound photographs . This help, cooperation and services are highly appreciated and acknowledged. Our thanks also due to Dr. Jyothi Subash, Dermatologist, Bangalore and for her views on this topic and we wish to express sincere thanks to Mr. Deepak L Student of Atria Institute of Technology for his support on this project.

10. REFERENCES

1. Clarke, J.A.: A Color Atlas of Burn Injuries. Chapman & Hall medical, London, (1992).

2. Serrano, C., Rao, L.M., Acha, B.: Evaluation of a Telemedicine Platform in a burn Unit. Proc. IEE Int. Conf. on Information Technology Applications in Biomedicine, Washington DC (USA) (1998) 121-126.

3. Roa, L.M., Gomez-Ciz, T., Acha, B., Serrano, C.: Digital Imaging in Remote Diagnosis of Burns. Burns, 7 (1999) 617-624.

4. Begona Acha, Carmen Serrano, Sergio Palencia, Juan Jose Murillo. Classification of burn wounds using support vector machines, (2001).

5. R. Gonzalez and R. Woods, “Digital image processing,” IEEE Transactions on Systems, Man, and Cybernetics, 2008.

6. Mathworks. (2010) Image Processing User guide. [Online]. Available: http://www.mathworks.com/help/pdf

7. Afromowitz, M.A., Van Liew, G.S., Heimbach, D.M.: Clinical Evaluation of Burn Injuries Using an Optical Reflectance Technique. IEEE Trans. on Biomedical Engineering, 2 (1987) 114-127.

8. Afromowitz, M.A., Callis, J.B., Heimbach, D.M., DeSoto, L.A., Norton, M.K.: Multispectral Imaging of Burn Wounds: A New Clinical Instrument for Evaluating Burn Depth. IEEE Trans. on Biomedical Engineering, 10 (1988) 842-850.

9. Hansen, G.L., Sparrow, E.M., Kokate, J.Y., Leland, K.J., Iaizzo, P.A.: Wound Status Evaluation using Color Image Processing.

10. Serrano, C., Acha, B., Acha, J.I.: Segmentation of Burn Images based on Color and Texture Information. SPIE Int. Symposium on Medical Imaging, 5032, (2003) 1543-1550, San Diego (CA, USA).

11. Image classification based on color and texture analysis. First intel workshop on Image and Signal Processing and Analysis June 14-15, 2000, Pula, Croatia.

12. J E Bennett R O Kingman “Evaluation of Burn Depth by the use of Radioactive Isotope- by An experimental study “, Plolic and reconstructive surgery, vol. 20, No.4, PP 261-272, 1957.

13. R. Duda, P. Hart, and D. Stork, “Pattern classification, ed, 2001.

14. Khalil Shihab, “A Back propagation Neural Network for Computer Network Security” in proceedings of Journal on computer Science, vol. 2, no.9, 2006, pp: 710-715.

15. Artificial Neural Network R.Yagna Narayana 2005.

16. Thira, J.P., Macq.B.: Morphological Feature Extraction for the classification of Digital Images of cancrous Tissues. IEEE.