An Improved Automated Malignant Melanoma Detection using Image Classification System

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***Abstract*— Melanoma is one of the deadliest form of skin cancer and its incidence rates have been increasing for the past three decades. The most important risk factor for Melanoma skin cancer is unprotected exposure to UV radiation. However, early diagnosis of malignant melanoma increases the chances for cure significantly. Therefore great effort has been put into the development of diagnosis method of melanoma. Thus a real time image analysis system to aid in the malignant melanoma prevention and early detection is highly in-demand. This project aims at detecting the best system of a real time image analysis system to aid in the malignant melanoma prevention and early detection. The system will analyse and process the images and alert the user at real-time to seek medical help urgently. This automated diagnosis of skin lesion and melanoma recognition can be greatly improve early detection of melanoma. The work introduces convenient steps for automating the process of melanoma prevention and detection. The proposed framework consist of major image processing techniques which results in higher accuracy. Experimental results on a PH2 dermoscopy research database images confirms the efficiency of the system. Parameters such as sensitivity and specificity are found out. Efficiency is increased using SVM classifier.**

Keywords—Image segmentation, lesion classifier, skin cancer, melanoma recognition, sensitivity and specificity.

I. INTRODUCTION

The increasing incidence of malignant melanoma cases over the last three decades has promoted the development of an automated system to aid in the malignant melanoma prevention and early detection. Among skin cancers forms, malignant melanoma is the most deadly form. However, early diagnosis of malignant melanoma increases the chances of cure significantly [1]. Therefore a real time image analysis system to aid in the malignant melanoma early detection is highly in-demand. a system that captures user environmental data (i.e. UV radiation level) and skin images and plugs it into the risk assessment system to alert the user at real-time to prevent risks associated with developing the skin cancer disease. It's important to note that one in five people will develop skin cancer in their lifetime, and on average, dies from skin cancer every hour. Cancer Society estimates that more than 76, 000 new cases of melanoma were diagnosed in 2012. This type of skin cancer is the less common, accounting for less than 5% of all skin cancer cases. However, it is by far the most aggressive since it is more likely to metastasize than other skin tumors. This characteristic makes melanoma the deadliest form of skin cancer (it is estimated that more than 75% of deaths related with skin cancer in 2012 will be from melanoma).

Melanoma incidence rates have been significantly increasing in the last decades, which makes this one of the cancers that has been receiving attention both from the public health field, with medical prevention campaigns, and from the cancer research field. The ultimate goal for physicians is to diagnose melanoma in its earliest stage, since it is less probable that it has already metastasized, thus greatly increasing the probability of survival. Nowadays, a technique used by dermatologists to diagnose skin lesions and, consequently, to detect melanomas is dermoscopy. This is a noninvasive procedure used for *in vivo* observation of skin lesions. The physician places gel on the skin lesion and inspects it with a magnification instrument (dermatoscope, stereomicroscope, or a digital imaging system), which amplifies the lesion 6–100×, depending on the instrument used [2].

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However, it has been demonstrated that dermoscopy only increases the diagnostic performance if the dermatologists have received formal training [7]. Moreover, even with the use of the described diagnostic algorithms, which aim to make the diagnosis more reliable and reproducible, the diagnosis of a skin lesion by a dermatologist is still subjective

since it depends on human vision and on clinical experience. Computerized dermoscopy image analysis systems can be used to tackle this problem. In these systems, a computer is used as a diagnostic tool and to follow up on suspicious skin lesions. If melanoma is found early, while it is still small and thin, and if it is completely removed, then the chance of cure is high. The likelihood that the melanoma will come back or spread depends on how deeply it has gone into the layers of the skin (Ahmed *et al.*, 2014).

A.OBJECTIVES

Objectives are:

1. Automate the image segmentation.
2. Improve the scope and accuracy of feature extraction techniques.
3. Create a comprehensive library of features that can be used to summarize the image.
4. Improve the performance of neural networks classification using novel multi-stage architectures.
5. Create an easy to use system/application that detects melanoma with a few simple steps.
6. Make the system widely available to physicians and dermatologists.

The skin represents the body's first line of defense against the exterior environment. As the largest organ of the human body, and since it covers the whole body, skin has the largest surface area with respect to all the others organs. It weighs more than any single internal organ, accounting for about 15 percent of body weight. It has many important functions that are critical to our well being. Skins prevent or reduce the attacks of viruses, bacteria, chemical substances and even ultraviolet light. It regulates body temperature by blood flow and evaporation through sweat. The secretion of sweat and skin lipid cause the elimination of a number of harmful substances resulting from internal metabolic activities. Also, skin protects the body from friction and impact wounds thanks to its flexibility and toughness. Furthermore, skin can act as a sensory organ as well, since it has a large amount of nerve fibers and nerve endings. When exposed to sunlight skin produce vitamin D, which is a necessary substance for the body. These functions of the skin tend to vary according to age, race, gender and individual health status. When the skin gets older, for example, it tends to lose its flexibility and toughness.

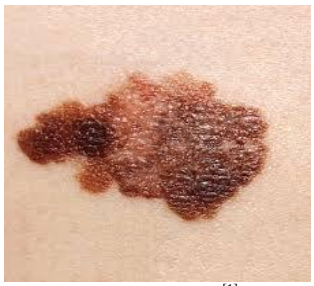


Fig.1. Melanoma[1]

II. RELATED STUDY

In skin health, diagnosis or diagnostics is the process of identifying a skin texture or problem by its signs, symptoms and the result of various diagnosis procedures. The conclusion reached through this process is called a diagnosis. The diagnosis system is a system that can be used to analyze any problem by answering some questions that lead to a solution to the problem. Skin cancer is a malignant tumor that grows in the skin cells and accounts for more than 50 percent of all cancers.

A. DETECTION USING ABCD RULE

In order to educate the masses to recognize melanoma in its early stages in 1985, group from New York University [3] devised the ABCD acronym (Asymmetry, Border irregularity, Color variegation, Diameter > 6mm). It is one of the easiest guides to the most common signs of melanoma. Further, Stolz, W. [7] established this diagnosis scheme for dermatoscopic images known as the ABCD rule of dermatoscopy. The characteristics needed to diagnose a melanoma as malignant are

(a**)** Asymmetry - Cancerous lesions are checked for symmetry. If the lesion is Symmetric (0 value) then it is benign (non-cancerous). For Cancerous cases asymmetry in zero, one (value 1)), or two orthogonal axes (value 2) are considered.

(b**)** Border irregularity – Most of the cancerous lesions edges are ragger, notched or blurred. Its value ranges 0 to 8.

(c**)** Color – Cancerous skin lesion's pigmentation is not uniform. The presence of up to six known colors must be detected - white, red, light brown, dark brown, slate blue, and black. Its value ranges 0 to 6.

(d) Diameter – Cancerous lesions are greater than 6mm wide. Differential structures with at least five patterns are relevant for specific types of lesions. Any growth of a mole should be of concern. Its value ranges 0 to 5.

Some melanomas do not fit the ABCD rule described above, so it is important for us to notice changes in skin markings or new spots on our skin. TDS (Total Dermatoscopy Score) Index [8] is an important tool used in the diagnosis of melanoma. Calculation of the TDS Index is based on Asymmetry, Border, Color and Diameter of the skin lesion. Asymmetry or A-factor has three values (symmetry – 0, 1-axis asymmetry – 1, 2-axis asymmetry - 2). Border or B-factor has 0 to 8 values. Color or C-factor has six values (Red, Blue, White, Black, light brown, dark brown). Presence of each color in the image leads to addition of value 1. Diameter or D-factor has 0 to 5 values. Any skin lesion with diameter greater than 6mm will be equal to value 5. The TDC Index is computed using following formula. It is also known as ABCD formula.

$$TDS = 1.3A + 0.1B + 0.\ 0.5C + 0.5D \quad (1)$$

If the TDS Index is less than 4.75, it is benign (non-cancerous) skin lesion. If TDS Index is greater than 4.75 and less than 5.45, it is suspicious case of skin lesion. If TDS Index is greater than 5.45, it is malignant melanoma (cancerous) skin lesion.

ABCD rule has proven more accurate and effectiveness in clinical practice with 76% diagnostic accuracy [9].But all melanomas do not have all four ABCD features. It is the combination of features (e.g., A+B, A+C, B+C, A+B+C, etc.) that render some lesions most suspicious.

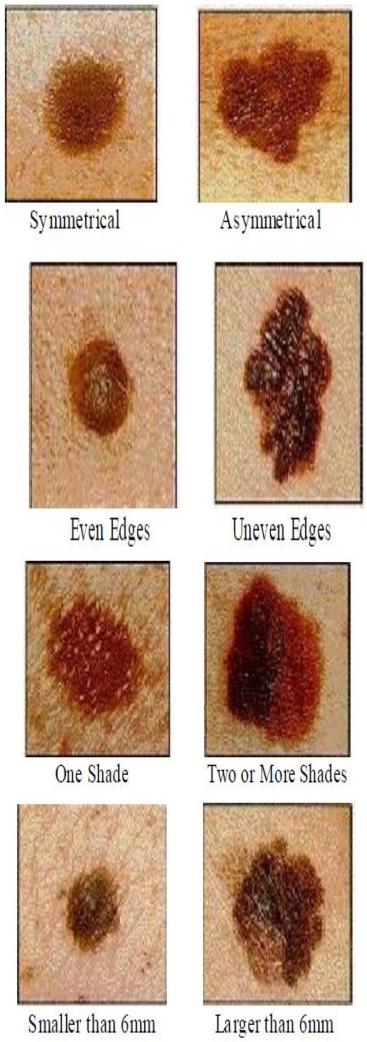


Fig.2. ABCD rule for detecting skin cancer

ABCD detection rule calculates certain parameters like assymettry index,border index, color index,diameter and TDS calculation. This ABCD rule became the standard in Dermoscopy for staging PSL into benign, suspicious, or malignant moles (melanoma). However, dermoscopic diagnosis is often complex and subjective, thus associated with poor reproducibility and low accuracy especially among inexperience dermatologist. Also, visual interpretations of these features by dermatologist have so far proven to be a difficult task. Detection rate based on clinical visual investigation to be about 65%.

B.DETECTION USING SVM CLASSIFIER

Support vector machine [9], is a supervised learning technique that seeks an optimal hyper plane to separate two classes of samples. Kernel functions are used to map the input data into a higher dimension space where the data are supposed to have a better distribution, and then an optimal separating hyper plane in the high dimensional feature space is chosen. The database is organized equally for Training set (Benign-10, Malignant-10) and Testing set (Benign-20, Malignant-20). The drawback in Support Vector machine is , it cannot classify more than two class classification. So, we propose the Multiclass Classification which combines the results of various binary SVM Classifiers. Multi class support vector machine with the combination of multiple binary classifiers are used to train and classify the random input images. SVMs are relatively new types of classification algorithms. An SVM expects a training data set with positive and negative classes as an input (i.e. a binary labeled training data set). It then creates a decision boundary (the maximal-margin separating boundary) between the two classes and selects the most relevant examples involved in the decision process (the so-called support vectors). The construction of the linear boundary is always possible as long as the data is linearly separable. If this is not the case, SVMs can use kernels, which provide a nonlinear mapping to a higher dimensional feature space. The main advantages of SVMs are that they are robust to outliers, converge quickly, and find the optimal decision boundary if the data is separable [7]. Another advantage is that the input space can be mapped into an arbitrary high dimensional working space where the linear decision boundary can be drawn. This mapping allows for higher order interactions between the examples and can also find correlations between examples. SVMs are also very flexible as they allow for a big variety of kernel functions. Sequential minimal optimization (SMO) [10] is used in this paper to train an SVM. SVMs have been shown to work well for high dimensional microarray data sets [10]. However, due to the high computational cost it is not very practical to use the Wrapper methods for SVM classification. The method showed satisfactory results but does not remove artifacts like hairs. The main parameters was also not calculated and also the data base used was so small which did not enable the proper classification of the images. The feature extraction was mainly done in the ROI mathematically.The overall perfomace of the system is very poor yielding to lower accuracy rate and lesser efficiency of classification.

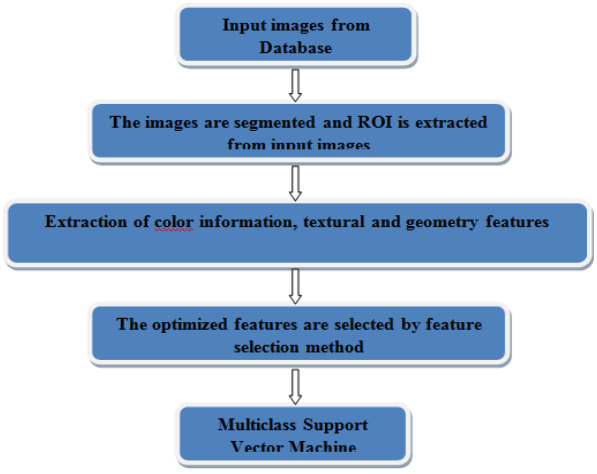


Fig.3.Block diagram of melanoma detection using SVM classifier.

C. TWO SYSTEM DETECTION OF MELANOMA

This paper addresses two different systems for the detection of melanomas in dermoscopy images. The first system uses global methods to classify skin lesions, whereas the second system uses local features and the bag-of-features classifier. It aims at determining the best system for skin

lesion classification. The other objective is to compare the role of color and texture features in lesion classification and determine which set of features is more discriminative. The first system describes the dermoscopy image by a set of global features and uses a classifier to discriminate

melanomas from non melanoma lesions. This is a supervised system since the classifier learns to detect the melanoma lesions using a training set of images, which is labeled by an expert. Each training image, i.e., $I(k)$, $k \in 1, \ldots, L$, is characterized by feature vector $\mathbf{x}k \in \mathrm{R}n$ and by binary label $yk \in \{0, 1\}$. The classifier is trained to discriminate both types of images using the training data $(\mathbf{x}k, yk)$, $k = 1, \ldots, L$.

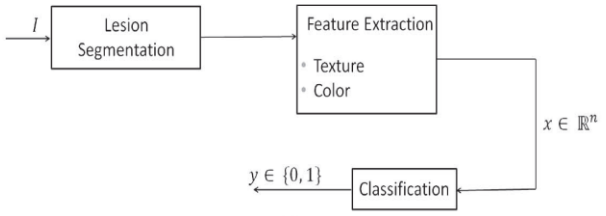


Fig.4.Block diagram of two system melanoma detection using global features

The second system characterizes the dermoscopy image by using a BoF approach. First, a set of keypoints is selected inside the lesion region. Then each keypoint is characterized by a vector of local features. This feature vector represents color and texture properties in a local patch centered at the key point. Since the number of key points and local features varies from image to image, cannot be directly feed a classifier with these data. Instead, all local features associated with all the training images are gathered and used to compute a smaller set of prototypes (centroids) denoted as *visual words*. Then, the local features of each dermoscopy image are assigned to the nearest visual word, and a histogram is computed. The histogram counts the number of times each visual word was selected. A statistical classifier is then trained to discriminate melanoma lesions from non melanoma ones, using the histogram of visual words as input. Image texture represents the spatial organization of intensity and colour in an image, and it can be characterized in many different ways. Some methods use pixel statistics. A classic approach consists in computing the statistics of pairs of neighbouring pixels, using the co-occurrence matrix [4]. This idea has been modified and improved in many different ways. For example, local binary patterns perform a binary classification of the pixels in the vicinity of each pixel and compute the statistics of the neighbouring pixel configurations [4]. Texture has been also described by applying a Fourier transform to the image and by characterizing the spectral energy in different frequency bands [5].

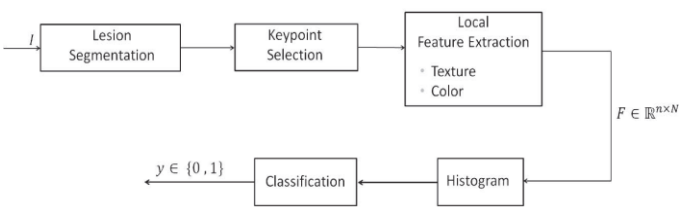


Fig.5.Block diagram of two system melanoma detection using local features

The major drawback of using this method is that it requires several number of systematic trials to calculate accuracy also accuracy is in the range of 75%.the value of specificity and sensitivity is less.since the system is not experienced more trails are required

D.SKIN RECOGNITION TECHNIQUE ON SMART PHONES

Skin image recognition on smart phones has become one of the attractive and demanding research areas in the past few years. Karargyris et al. have worked on an advanced image-processing mobile application for monitoring skin cancer [3]. The authors presented an application for skin prevention using a mobile device. An inexpensive accessory was used for improving the quality of the images. Additionally, an advanced software framework for image processing backs the system to analyze the input images. Their images database was small, and consisted of only 6 images normal cases and 6 images of suspicious case. Wadhawan, et al. proposed a portable library for melanoma detection on handheld devices based on the well known bag-of-features framework [4]. They showed that the most computational intensive and time consuming algorithms of the library, namely image segmentation and image classification, can achieve accuracy and speed of execution comparable to a desktop computer. These findings demonstrate that it is possible to run sophisticated biomedical imaging applications on smart phones and other handheld devices, which have the advantage of portability and low cost, and therefore they can make a significant impact on health care delivery as assistive devices in underserved and remote areas. However, their system didn't allow the user to capture images using the smart phones.[11]. Experimental result showed that the system was not highly efficient, achieving an average accuracy of 66.7%, with average malignant class recall/sensitivity of 60.7% and specificity of 80.5<%.

E.SKINcure application

SKINcure application is a smart phone-based application for iPhone or iPod with iOS 7.0 and onwards that will give the user live access to the current UV index and allow the user to calculate the time to skin burn with given parameters. The aspirant feature of this application is Dermoscopy Image Analysis that analyzes the dermoscopy skin images of the users and provides skin cancer protection guidelines.

The core functionalities of the SKINcure application are as follows:

1. Provide and show graphical representation of local UV status.
2. Calculate the time to skin burn and set notification alert.
3. Create and manage users mole images profile for dermoscopy analysis
4. Perform dermoscopy image analysis using a remote image processing server.

The application is designed in a well-defined structure ensuring quality user experience for using the application features. The apps gives the UV index level and the the time to skin burn,but doesn’t not give an idea about the type of melanoma.

III. PROPOSED METHOD

In proposed system, the user will be able to capture images of skin moles as well as certain environmental metrics (e.g. UV radiation). One component of our system is an image processing module to classify under which category the moles fall into; normal, typical or melanoma. An alert will be provided to the user to seek medical help if the mole belongs to the atypical or melanoma category. The outcome of this platform is intended to help users prevent developing skin cancer by triggering a real-time alert that informs the users to 1) avoid exposure to harmful UV radiation and 2) early detection of malignant melanoma which increases the chances of successful treatment. system will analyze and process the images and classify the images to normal, atypical and melanoma cases based on extracting certain image features.It introduces convenient steps for automating the process of melanoma prevention and detection and as a result, can alert the user at real-time to seek medical help urgently.

It is important to note that unprotected exposure to ultraviolet (UV) radiation is the most threatening risk factor for skin cancer [7]. Skin should be protected from intense sun exposure all the time. In proposed system, PH2 dermoscopic image database from Pedro Hispano hospital is used for the development of our system and for testing purposes [9]. The dermoscopic images were obtained under the same conditions using a magnification of 20x[9]. This image database contains a total of 200 dermoscopic images of lesions, including 80 normal moles, 80 atypical and 40 melanomas. They are 8-bit RGB color images with a resolution of 768x560 pixels.And the efficiency can be calculated by using this dermoscopic database

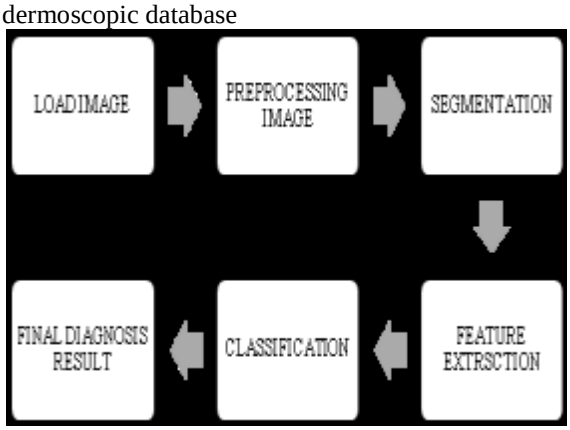


Fig.6.Basic block diagram for melanoma detection

A.PREPROCESSING

Preprocessing is the first stage of detection system helps to enhance the quality of an image by noise removal, unwanted illumination and contrast enhancement. The enhanced image is used for feeding the next step.the salt and pepper noise is removed by median filter

B.SEGMENTATION

The first aim of this paper is to build an efficient robust automatic segmentation tool for skin lesion images. It can be noticed that the lesions have large variations in size as well as in color and contrast to the surrounding skin. In order not to lose any important structures within the lesion, gray-scale morphology is used to derive the segmentation. Active-contours methods have already been used to segment pigmented skin Lesion images. However, usually a conversion to a grayscale image precedes the processing stages. It extracts object at a high contrast against a background and for distinguishing smooth forms. The primary condition is the initialization of the contour. This significantly influences the final result. In case of variations in a mass, it is not easy to recognize the size, form, and position of the target, and in such cases, even if it is not desirable, the initial contour must be set up manually.

Thus a color based segmentation is used here based on pixel orientation is being made used.The three color channels are then converted into grey scale image which is used for further processing. The performance of colour segmentation significantly affects the quality of an image understanding system.the colors in three channels are merged and is converted to binary image of black and white.

In this framework, it proposes two types of classifiers, i.e. one level classifier and two-level classifier. The first stage of this framework is to perform image processing to denoise the image and to segment the Region of Interest (ROI) of the skin. After segmenting the ROI, extracting the image features like 2-D Fast Fourier Transform features set (FFT2), 2-D Discrete Cosine Transform features set (DCT2), size and complexity features sets. Next is to feed the extracted features to the classifiers. Which are of two types of classifiers: One level classifier and Two-level classifier. In the one level classifier, only one classifier is used to classify the ROI into three categories, normal, atypical or melanoma. However, in the two-level classifier two classifiers, are used, i.e. classifier I and classifier II. Classifier I classifies the image into normal or abnormal, and classifier II classifies. abnormal ROIs into atypical or melanoma the two-level classifier approach gives better result k-Nearest Neighbor (kNN) classifier is used as a single level classifier and SVM is used as a two level classifier. In the experiments, 75% of the database used for training and 25% is used for testing .the 2-D Fast Fourier transform (FFT) feature set [10] computes the Discrete Fourier transform (DFT) and its inverse.

C.FEATURE EXTRACTION

A 2-D Discrete Cosine Transform (DCT) [11] expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. As a result, 2-D FFT and 2-D DCT are widely used for many applications. Therefore, we used such features to classify the malignant melanoma cases. The 2-D FFT feature set includes the first pixel of FFT2, the first pixel of the cross-correlation [12] of the first 20 rows and columns of FFT2, the mean of the first 20 rows and columns of FFT2, and the standard deviation of the first 20 rows and columns of FFT2. The 2-D DCT feature set includes the first pixel of DCT2, the first pixel of the crosscorrelation of the first 20 rows and columns of DCT2, the mean of the first 20 rows and columns of DCT2 and the standard deviation of the first 20 rows and columns of DCT2. The complexity features set includes the image ROI's mean, standard deviation and mode based on the intensity information.

D.CLASSIFIER

Two classifications are done here using two different efficient classifiers,such as k-nn (k-nearest neighbor)Classifier as one level classifier and SVM(Support Vector Machine) as the two level classifier which further classifies the data base images into its counter parts.

1.K-nn classifier

In pattern recognition, the k-Nearest Neighbors algorithm (k-NN) is a non parametric method used for classification. Here the input consists of the k closest training examples in the feature space. In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. KNN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms. Based on the output of KNN classifier, the severity stage of skin cancer is detected whether it is normal,atypical or melanomic.

2.SVM CLASSIFIER

In machine learning, support vector machines 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.Here,in two level classifier,first classifier classifies into normal or abnormal,then the abnormal images are again classified to the same svm classifier to obtain whether it is an atypical lesion or melanomic lesion.

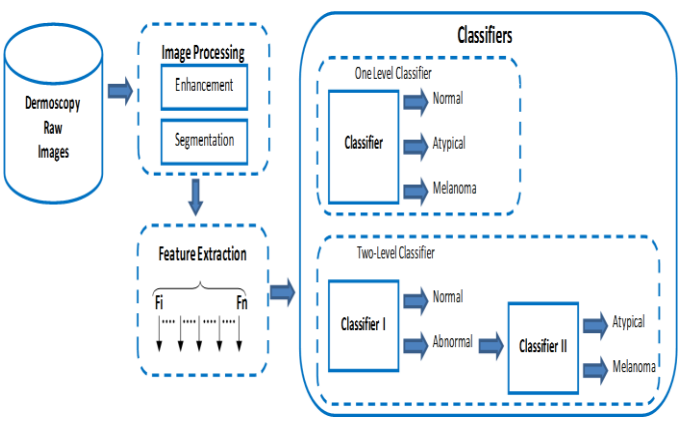


Fig.7.Proposed method

IV.PERFORMANCE MEASURES

1.Accuracy

The accuracy of the classifier is the percentage of the test samples that are correctly classified by the classifier.

$$Accuracy = TP+TN / TP + FP + FN + TN \quad (2)$$

2.Sensitivity

It is also referred as true positive (TP) rate that is the propagation of positive samples that are correctly identified.

$$Sensitivity = TP / TP+FN \quad (3)$$

3.Specificity

It is the true negative (TN) rate that is the proportion of negative samples that are correctly identified

$$Specificity = TN / TN + FP \quad (4)$$

[TP – True Positive, TN – True Negative, FP – False Positive, FN -False Negative]

4.CONFUSION MATRIX

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known.

V.EXPERIMENTAL RESULTS

Database consists of 12 digital images, where 4 each of normal,atypical and melanoma .The image processing techniques are done and corresponding results hav been acquired and the performance measures are calculated inorder to confirm the efficiency of the system.

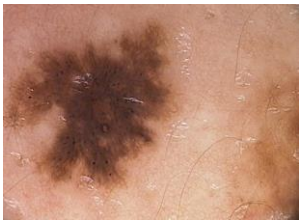


Fig.8.Melanoma image

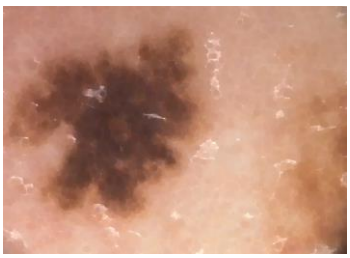


Fig.9:image enhancement

Fig.10.Binary segmentation

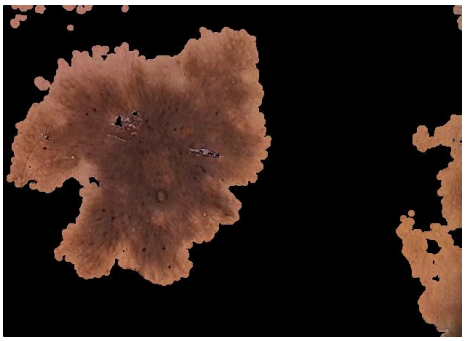


Fig.11.Desired image

1.RESULTS OF ONE LEVEL CLASSIFIER

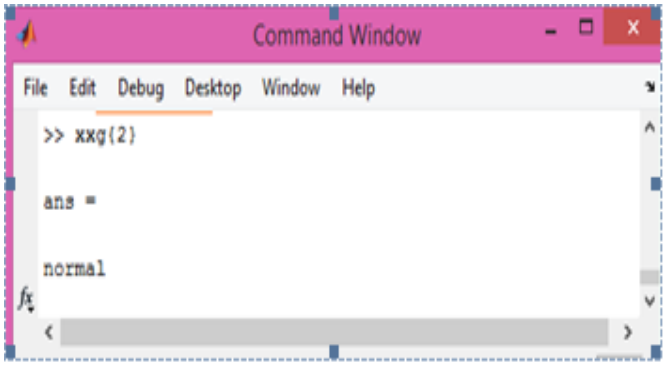


Fig.12.normal type of classifier 1

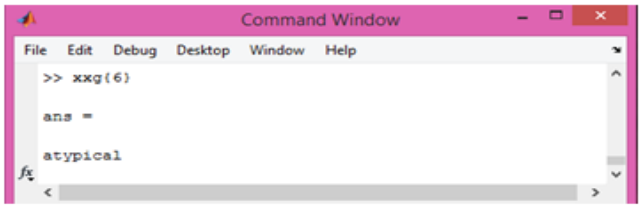


Fig.13.atypical type of classifier 1

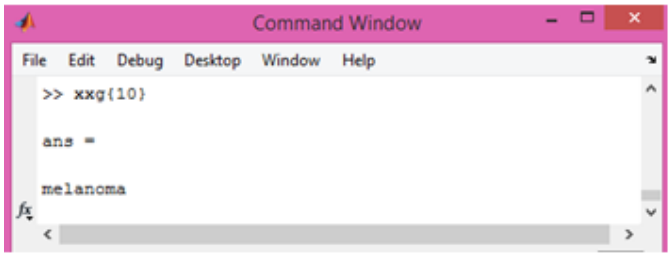
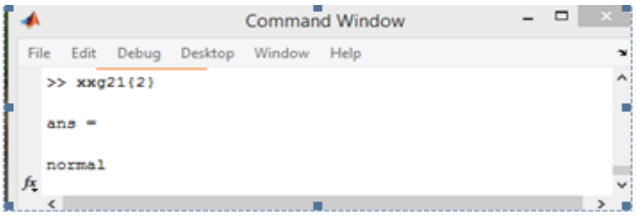
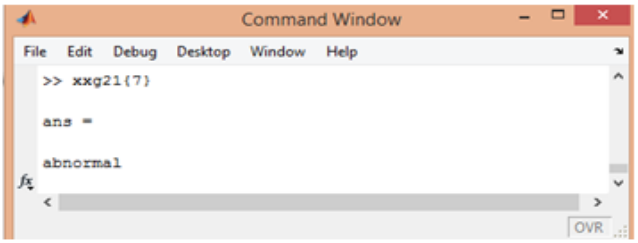


Fig.14.melanoma type of classifier one

2 .RESULTS OF TWO LEVEL CLASSIFIER



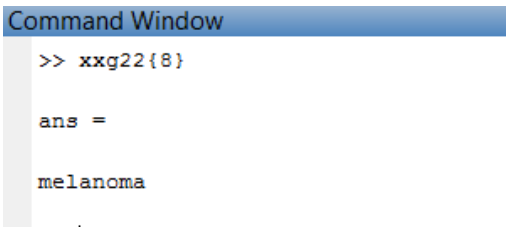
(a)



(b)

Fig.15(a),(b).Result of classifier 1 in two level classifier

(a)



(b)

Fig.16(a),(b).Result of classifier 2 in two level classifier

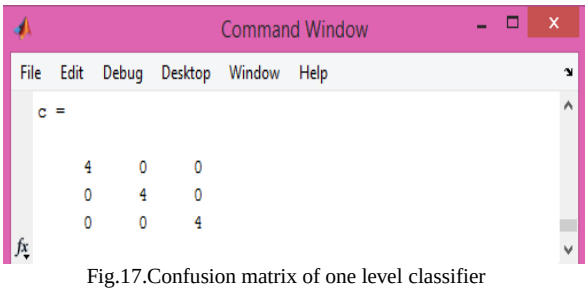


Fig.17.Confusion matrix of one level classifier

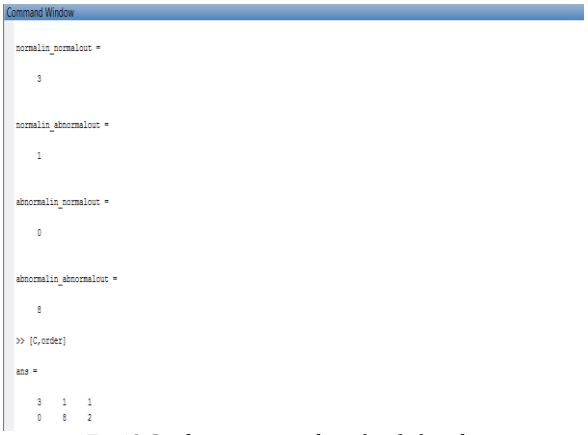


Fig.18.Confusion matrix of two level classifier

TABLE 1 PARAMETERSCALCULATED

SENSITIVITY	100
SPECIFICITY	100
ACCURACY	100

For malignant melanoma detection the usage of both k-nn and SVM Classifier together yields an accuracy and efficiency of 100.the results are perfectly classified based on its type.

VI.CONCLUSION

A novel framework to classify the dermoscopic images into normal, atypical and melanoma. In particular, the framework compared the performances of two classifier techniques, one level classier and two-level classifier. It is concluded that the two-level classifier outperforms the one level classifier. Future work will focus on defining and extracting novel features, for example pigment network and shape geometry feature set, to improve the accuracy of classification, as well as integrating the image classification module with the UV radiation module to complete the skin cancer risk assessment procedure. In addition, more sophisticated pattern recognition methods can also be used. From the results obtained, we can see our proposed method received a better quantity rate for all input images.

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