RECOGNITION OF SKIN CANCER IN DERMOSCOPIC IMAGES USING KNN CLASSIFIER

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ABSTRACT

The largest organ of the body is human skin. Melanoma is a fastest growing & deadliest cancer which starts in pigment cells (melanocytes) of the skin that mostly occurs on the exposed parts of the body. Early detection is vital in treating this type of skin cancer but the time and effort required is immense. Dermoscopy is a non invasive skin imaging technique of acquiring a magnified and illuminated image of a region of skin for increased clarity of the spots on the skin The use of machine learning and automation of the process involved in detection will not only save time but will also provide a more accurate diagnosis. The skin images collected from the databases cannot be directly classified by the automation techniques. The reason is twofold: (a) Lack of clarity in the features which is mainly due to the poor contrast of the raw image and (b) Large dimensions of the input image which causes the complexity of the system. Hence, suitable techniques must be adopted prior to the image classification process to overcome these drawbacks. The first drawback can be minimized by adopting suitable pre- processing techniques which can enhance the contrast of the input images. The second drawback is solved by incorporating the feature extraction technique which reduces the dimensions of the input image to high extent. Further, K-NN (K-Nearest Neighbor) classifier is used for classification of the given image into cancerous or non- cancerous.

KEYWORDS

Dermoscopy , Melanocyte , Histogram

1. INTRODUCTION

The skin is the important organ that covers the whole human body. Many people do not think of the skin as like other organs, it has a discrete structure and many important functions. Skin has mesodermal cells, pigmentation, such as melanin provided by melanocytes, which absorb some of the potentially dangerous ultraviolet radiation (UV) in sunlight. It also contains DNA repair enzymes that help reverse UV damage, such that people lacking the genes for these enzymes suffer high rates of skin cancer. One form predominantly produced by UV light is malignant melanoma, is particularly invasive, causing it to spread quickly, and can often be deadly. Skin cancer is the common of all human cancers. Some form of skin cancer is diagnosed in more than 3 million people in the United States each year. Cancer occurs when normal cells undergo a transformation during which they grow abnormally and multiply without normal controls. As the cells multiply, they form a mass called a tumor. Tumors of the skin are referred to as skin lesions. This means that they encroach on and invade the neighboring tissues because of

their uncontrolled growth. Tumors may also travel to remote organs via the bloodstream or lymphatic system. Melanoma is a cancer of pigment producing-cells called melanocytes. Most melanomas originate from the skin, though they can also arise from other parts of the body containing melanocytes, including the eyes, brain or spinal cord, or mucous membranes. The ability to spread widely to other parts of the body is a unique characteristic of melanoma that the other more common skin cancers, basal cell carcinoma and squamous cell carcinoma, rarely possess. This characteristic makes melanoma the deadliest of all skin cancers. Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality. Skin cancer can be cured at very high rates with simple and economical treatments, if detected at its earlier stages. Presently there is a greater need of automatic and cost effective emergency support system for the diagnosis of skin cancer at an early stage. Recently, computer-aided diagnosis (CAD) has become a part of the routine clinical work for detection of skin cancer at many screening sites and hospitals in the United States. This seems to indicate that CAD is beginning to be applied widely in the detection and differential diagnosis of many different types of abnormalities in medical images obtained in various examinations by use of different imaging modalities. The future of image processing and CAD in diagnostic is more promising now than ever, with increasingly impressive results.

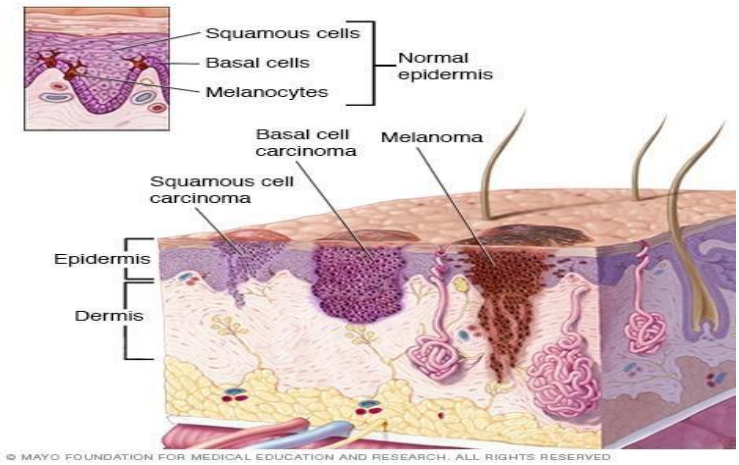


Figure 1: Structure of the skin with cancer cells

2. RELATED WORK

Related work introduce some research for automatic benign and malignant skin lesion detection in the following.

Noel C. F. Codella , Chung-Ching Lin, Proposes an Automated dermoscopic image analysis that has witnessed rapid growth in diagnostic performance. Yet adoption faces resistance, in part, because no evidence is provided to support decisions. In this work, an approach for evidence-based classification is presented. A feature embedding is learned with CNNs, triplet-loss, and global average pooling, and used to classify via k-NN search. Evidence is provided as both the discovered neighbors, as well as localized image regions most relevant to measuring distance between query and neighbors. To ensure that results are relevant in terms of both label accuracy and human visual similarity for any skill level, a novel hierarchical triplet logic is implemented to jointly learn an embedding according to disease labels and non-expert similarity. Results are

improved over baselines trained on disease labels alone, as well as standard multiclass loss. Quantitative relevance of results, according to non-expert similarity, as well as localized image regions, are also significantly improved.

Margarida Silveira, Dermoscopic images are detected using an intelligent agent-based or robotic system to conduct long-term automatic health monitoring and robust efficient disease diagnosis as autonomous e-Careers in real-world applications [2]. In this research, the aim is to deal with such challenges by evaluating six methods for the segmentation of skin lesions in dermoscopic images. They includes some state of the art techniques which is being successfully used in many medical imaging complications (gradient vector flow (GVF) and the level set method of Chan et al. [(C-LS)]. They also provides a set of methods introduced by the authors which are combined with this certain application (adaptive thresholding (AT), adaptive snake (AS), EM level set [(EM-LS), and fuzzy-based splitand-merge ssss algorithm (FBSM)]. The segmentation methods has been applied to 100 dermoscopic images and they are further evaluated with their respective four different metrics, with the particular segmentation result they provides an experienced dermatologist as the ground truth. The best results were obtained by the AS and EM-LS methods, which are semi-supervised methods. The fully automatic method is FBSM, where the results is slightly poor than AS and EM-LS.

Omar Abuzaghleh, a real time image analysis system [3] to aid in the malignant melanoma prevention and early detection is highly in-demand. In this paper, they proposed a real time image analysis system to recover the malignant melanoma prevention and their early detection. They present an image recognition technique, where the user will be able to capture skin images of different mole types and the system will analyze and process the images and inform the user at real-time to have a medical help urgently. This work introduces convenient steps for automating the process of melanoma prevention and detection. Experimental results on a PH2 dermoscopy research database images confirms the efficiency of the system.

3. PROPOSED SYSTEM

Proposed System, It is an intelligent decision support system for benign and malignant skin lesions classification. The system includes the following key stages, i.e. pre-processing, skin lesion segmentation, feature extraction and classification. Figure 2 shows system architecture, which shows the principal processes of the proposed system. The test image is preprocessed which includes hair removal, enhancement and morphological operation. We can remove noise, sharpen the details of the infected region and adjust the contrast of an image, making it easier to identify key features using Morphological operations. In Segmentation, Adaptive Thresh-holding is used. In Feature Extraction, different algorithms were used, they are Mean (Fast Fourier Transmission), Standard Deviation(FFT), Histogram based Mean & Standard Deviation, Edge based pixel count of area & hole and Edge based logarithmic pixel count of area & hole. This is an important distinguishing feature characteristic for diseases. For the classification K-NN (K-Nearest Neighbor) is used. The K-NN classifier are applied on the statistical texture features to predict the malignancy of the skin lesion. Each skin image in test set is classified by comparing it against the skin images in the training set. The training set consists of both normal and cancer skin images and skin disease images. The comparison is performed using the local features obtained in the previous step. K-NN have several advantages over the more classical classifiers such as decision trees and neural networks. The following section describes the modules involved in the proposed work.

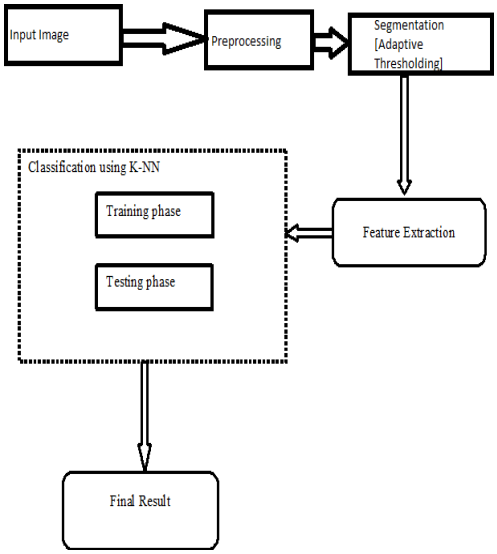


Figure 2: System Architecture for the proposed work

4. METHODOLOGY

The following steps are implemented for classification of skin cancer

- Image Acquisition
- Pre-processing
- Segmentation
- Feature Extraction
- Classification

4.1. Image Acquisition

Input to proposed system is dermoscopic images, dermoscopic images are images taken by dermatoscope. It is a hand held instrument used to take pictures of skin lesions (body part) and make it very easier to diagnose skin disease. These images were obtained from online skin diseases gallery namely ISIC 2018 database, Dermquest.com and skinvision.com

4.2. Pre-Processing

Preprocessing of the skin image is the first step in authors proposed technique. Usually skin images have pathological noise and various texture backgrounds, which may cause difficulties in extraction. Preprocessing of an image is done which involves two steps, they are

1. Hair removal
2. Image enhancement

The purpose of these steps is basically to improve and enhance the image and the image quality to get more surety and ease in segmenting the skin lesion. Hence Morphological “closing” operation

is performed to pursues the goals of filtering out the form and structure of the image.

4.2.1. Morphological Operation

Morphology is a broad set of image processing operations that process skin images based on shapes and making it easier to remove noise, hair and adjust the contrast of an image. The most basic morphological operations are Dilation & Erosion were used.

- **Dilation -** It allows skin lesions to expand, thus potentially filling in small holes and connecting disjoint objects.

- **Erosion -** It shrinks the skin lesion by etching away (eroding) their boundaries. The holes and gaps between different regions become larger, and small details are eliminated

An essential part of the dilation and erosion operations is the structuring element used to probe or interact the given image. A structuring element is a shape which is represented by a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. The pixels with values of 1 define the neighborhood. Structuring elements are typically much smaller than the image being processed. The center pixel of the structuring element, called the *origin*, identifies the pixel of interest i.e., the pixel being processed. These pixels are considered in dilation and erosion processing.

In the proposed work, A disk shaped structuring element was used as this shape reflects biological structures more accurately than sharp angles or linear shapes. Disks are a natural choice for a structuring element, since they are **isotropic** (same in all directions), disk radius value is assigned as r=6. The first operation is **Closing** it is a dilation followed by an erosion. Closing smoothes the contour by enforcing bridges and closing small holes. Since dilation occurs, small holes are removed as the inner lining of the shapes fill inward. The restoring erosion will skip the closed holes, thus making this operation good for closing up holes. Thus morphological filtering helps as to smooth and simplify the objects edges without changing the size of objects and enhance the particular melanoma region for accurate segmentation.

4.3. Segmentation

segmentation has become an important part of image processing. The main aim of segmentation is simplification i.e. representing the skin image into meaningful and easily analyzable way. The main objective behind the segmentation of the medical image is to separate the tumor from the background. Using the thresholding method, segmentation of the skin lesion is done by fixing all pixels whose intensity values are more than the threshold to a foreground value. The remaining pixels are set to a background value. Such technique can be used to obtain binary images from grayscale images. The conventional thresholding techniques use a global threshold for all pixels, whereas adaptive thresholding changes the threshold value dynamically over the image. In this phase, adaptive thresholding is used to extract the skin image.

4.3.1. Adaptive Thresholding

In this, the algorithm calculate the threshold for a small regions of the image. Obtaining different thresholds for different regions of the same image and it gives us better results for images with

varying illumination. Using local adaptive thresholding, each pixel in the image will have its own threshold value to segment the tumor from the background. Adaptive thresholding typically takes a grayscale or color image as input and, in the simplest implementation, outputs a binary image representing the segmentation. For each pixel in the tumor image, a threshold has been calculated using standard deviation. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value. As adaptive thresholding creates separate threshold value for every segment in the image. The minimum threshold value is chosen for segmentation.

A threshold T(x, y) is a value such that

$$\mathbf{b(x,y)} = \begin{cases} \mathbf{0} \ \boldsymbol{if}\ \boldsymbol{I(x,y) \le T(x,y)} \\ \mathbf{1} \qquad\qquad \boldsymbol{otherwise} \end{cases}$$

Where b(x,y) is the binarized image and I(x,y)∈[0,1] be the intensity of a pixel at location (x,y) of the image I. In local adaptive technique, a threshold is calculated for each pixel, based on some local statistics such as range, variance, or surface-fitting parameters of the neighborhood pixels. It can be approached with standard derivation of pixel values, and local image contrast.

4.4. Feature Extraction

Feature extraction is often a necessary step for segmentation to be successful. Lesions come in different sizes and have different properties. To classify images into those that display benign traits or melanoma, features need to be extracted to be fed into the classification stage. Here, the skin mole is converted to intensity values by a vector of features and its dimension depends on the number of extracted properties. This involves the computation of several statistical properties to yield features. These features were then considered as a source data for the subsequent stages. Features have been then extracted from the segmented dermoscopic lesions. Some mathematical terms were used for finding the parameters like mean, s.d.

The selected features are elaborated below

4.4.1. Fast Fourier Transform

The FFT are applied to tumor images for the purpose of enhancing visibility or selection of features or structures of interest for measurement (such as image compression, motion characteristics measurement, data loss analysis, etc). In the realm of image processing the fourier transform basically breaks down the image into the frequency domain. This makes it much easier to process and concentrate purely on discrete components of an image and also could isolate out the particular portion of the image easily. Creating a magnitude spectrum which specifies the mean and standard deviation. Visualizing the fourier transform image using matlab is given below

$$\mathbf{F(u,v)} = \sum_{x=0}^{M-1} \boldsymbol{f(x,y)W_M^{ux}}$$

- F(u,v) is a Fourier transform of f(x,y) and it has complex entries. F = fft2(f)

- In order to display the Fourier Spectrum |F(u,v)|
  - Reduce dynamic range of |F(u,v)| by displaying the log: D = log(1+|F(u,v)|)

4.4.2. Histogram Based Mean & Standard Deviation

The histogram provides information about the nature of the melanoma, or an object within the skin image. The histogram calculation is a fully statistical approach, so we perform quantization. Quantization is a process in which the histogram is divided into levels or bins. As grayscale image consists of 256 levels. Computations for the feature extraction in these 256 levels will be slow. To increase the speed of computations, the histogram of the skin image is reduced to 2 bins. Then the mean and standard deviation of pixels in each bin is been calculated, because the mean will give an idea about the brightness of the image and the standard deviation give an idea about the contrast of the skin image

Mean: It is the measure of intensity. The value of the Mean shows the general brightness of the image. Each bin consists of a range of some pixel values. These values in each bin can be used to calculate the mean of bin which represents the brightness of the image in that bin. If mean of a bin is high then it means that the image is bright in that bin and if mean is low then it means that the image is dark in that bin. The mean is defined as:

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{ji}$$

Standard Deviation: It is the measure of contrast in an image. The standard deviation in each bin is also calculated by using the mean and pixel values of each bin. The standard deviation reveals something about the contrast of the skin image in particular bin. If standard deviation is high then it shows the high contrast of melanoma in a particular bin. If standard deviation is low then it will show the low contrast in melanoma of a particular level of histogram. The SD is defined as:

$$\sigma_j = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{ji-\mu_j})^2}$$

x_{ji} is the pixel values in the bin
N is the total number of pixels in each bin.

4.4.3. Edge Based Features

Edge based features of the skin lesions are calculated. In which they includes four parameters (pixel count of hole, pixel count of edge and taking logarithm for both hole & edge).In edge-based description, edge (or contour) pixels could be expressed by their coordinates, sequence, or by geometrical properties of the surrounded region (such as boundary length, curvature, and signature).

4.4.4. Pixel count of hole & edge

Edge pixels are detected for each area to describe the location and the intensity level of the

corner. Holes are bounded **contiguous pixels** (regions) and have a distinct intensity level. If a region (e.g., a surface) has holes, it is called as multiple contiguous region. Holes could be classified into circular (elliptical), polygonal, and irregular holes. The basic hole & edge feature measurements are area. Moments define the object pixels distribution with *M* as the total area of region (such as hole) is defined by:

$$\mathbf{M} = \sum_i \sum_j \boldsymbol{I}\,(\boldsymbol{x_i}, \boldsymbol{y_j}),\ \mathbf{(i,j)} \boldsymbol{\epsilon R}$$

Where *R* is the region of interest and (*i, j*) represents the pixels of the region.

4.5. Classification

Selected features are used for the recognition and classification of skin lesions. A wide range of classifiers is explored. Eventually, the K-NN classifier was used for skin lesion classification because of its superior performances. KNN classifier is best suited for classifying skin images due to its lesser execution time and better accuracy than other commonly used methods which include Hidden Markov Model and Kernel method. KNN classifier has a faster execution time and is dominant than SVM.

4.5.1. KNN Classifier

The simplest classification scheme is a nearest neighbor classification in the image space. Under this scheme an image in the test set is recognized by assigning to it the label of the closest point in the learning set, where distance are measured in image space. The Euclidean distance metric is often chosen to determine the closeness between the data points in KNN. A distance is assigned between all pixels in a dataset. Distance is defined as the Euclidean distance between two pixels. This Euclidean distance is by default in a KNN classifier. After the feature extraction process, the extracted features are directly applied to the classifiers, the machine learning tools, for classification into two different classes. The process involves two phases namely training phase and testing phase.

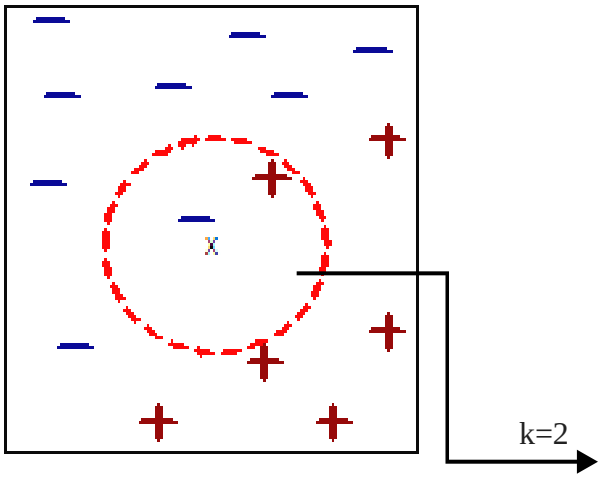
- **Training phase:** The patterns in terms of features and class labels of benign or malignant images are fed to the classifiers for training. The sample images of about 40 melanoma(type = 1) and 40 normal(type = 0) skin images are trained with their feature attributes which has been extracted during feature extraction. And these datas were plotted in the feature space.

- **Testing phase:** Unknown test pattern is fed and the knowledge gained during the training phase will classify the unknown pattern and again plot them in the feature space. A *feature space* is an abstract space where each sample image with their attributes is represented as a point in n- dimensional space. Its dimension is determined by the number of features used to describe the patterns. The total number of images in the training database is 40.

4.5.2. Parameter Selection

The best choice of *k* depends upon the data; generally, larger values of *k* reduces effect of the noise on the classification, but make boundaries between classes less distinct. A good *k* can

be selected by various heuristic techniques. The special case where the class is predicted to be the class of the closest training sample is called the nearest neighbor algorithm. The accuracy of the *k*-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the feature scales are not consistent with their importance. Much effort has been put into features



to improve classification. Here k value is taken as 2.

Figure 3: K- Nearest Neighbor feature space with k=2

In the fig3, it is shown that '–' negative symbols are melanoma(type=1) and '+' positive symbols indicate normal skin image(type=0) which are trained with KNN and plotted in the feature space with value k=2. Here '×' symbol indicates an unknown sample, which is been plotted in the feature space and now compute the nearest distance as the value of k is set as 2. Use class labels of nearest neighbors to determine the class label of unknown sample image. In the above fig, symbol '×'(unknown sample) is nearest to '–' (melanoma type=1) which indicates the presence of melanoma. Likewise, the sample images are classified and analysed as benign or melanoma skin cancer.

Advantage: The KNN is an unbiased algorithm and have not any assumption of the data under consideration. It is very popular because of its simplicity and ease of implementation plus effectiveness. A main advantage of the KNN algorithm is that it performs well with multi-model classes because the basis of its decision is based on a small neighborhood of similar objects. Therefore, even if the target class is multi-modal, the algorithm can still lead to good accuracy.

5. EXPERIMENTAL RESULT

The proposed method detailed in (4) is applied on the 100 dermoscopic images. The database contains 42 non-melanoma (benign) and 58 melanoma (malignant) images. The feature values are extracted for the sample images and classification is performed using KNN classifier which includes training and testing of the skin images. The performance analysis graph is shown below

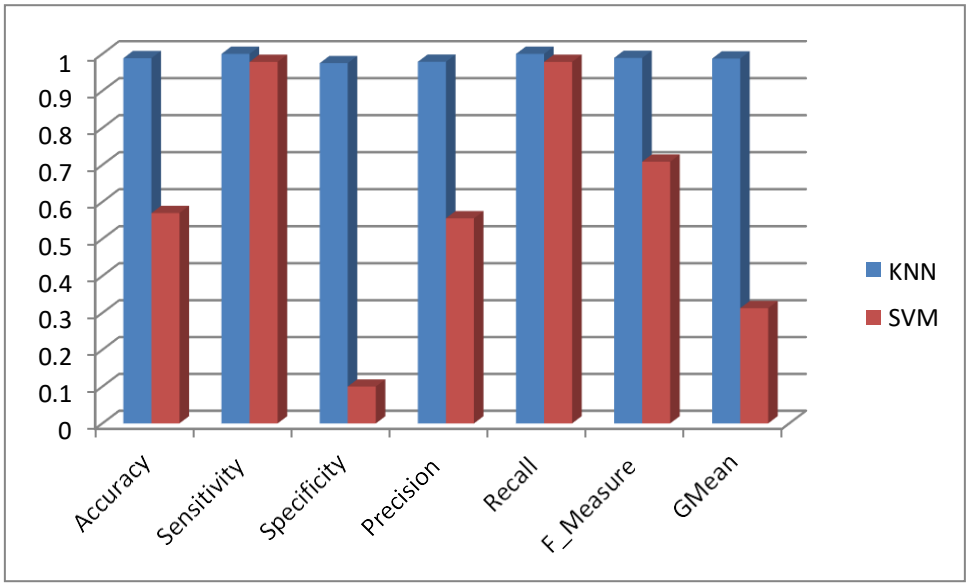


Figure4: Analysis graph

5.1. Performance Analysis

To analyze the performance metrics of the proposed architecture, The results of K-NN is compared with SVM respectively. Some of the performance metrics are given below,

5.1.1. Accuracy: The accuracy of a test is its ability to differentiate the healthy and melanoma skin images correctly. To estimate the accuracy, it is necessary to calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

5.1.2. Sensitivity: (also called the true positive)The sensitivity of a test is its ability to determine the benign cases i.e., healthy correctly. To estimate it, the proportion of true positive in sample images is been calculated. Mathematically, this can be stated as:

$$\text{Sensitivity} = \frac{No\ of\ TP}{No\ of\ TP+FN}$$

5.1.3. Specificity: The specificity of a test is its ability to determine the healthy cases correctly. To estimate it, the proportion of true negative in healthy cases is been calculated. Mathematically, this can be stated as:

$$\text{Specificity} = \frac{No\ of\ TN}{No\ of\ TN+FP}$$

5.1.4. Precision: Precision (also called positive predictive value) is the fraction of relevant instances among the retrieved instances.

$$\text{Precision} = \frac{TP}{TP+FP}$$

5.1.5. Recall: It (also known as sensitivity) is the fraction of relevant instances that have been retrieved over the total amount of relevant instances. Both precision and recall are based on an understanding and measure of relevance.

$$\text{Recall} = \frac{TP}{TP+FN}$$

5.1.6. F-measure: A measure that combines precision and recall and is the harmonic mean of decision and recall. Here β parameter on F-measure has zero value.

$$\text{F-measure} = \frac{(\beta^2+1) \times sens \times prec}{sens + \beta \times prec}, \beta \geq 0$$

5.1.7. G-mean: It is the geometric mean of sensitivity and precision.

$$\text{G-mean} = \sqrt{sens \times prec}$$

- True positive(TP) = correctly identified
- False positive(FP) = incorrectly identified
- True negative(TN) = correctly rejected
- False negative(FN) = incorrectly rejected

Comparison metrics between SVM and K-NN

Comparison Metrics	SVM	K-NN
Accuracy	0.5698	0.9884
Sensitivity	0.9783	1
Specificity	0.1	0.975

Precision	**0.5556**	**0.9787**
Recall	**0.9783**	**1**
F-measure	**0.7087**	**0.9892**
G-mean	**0.3128**	**0.9874**

Table 1: Comparison metrics of SVM & K-NN

Table 1 shows the performance metrics of the proposed method with recent works on classification and recognition of melanoma. Authors proposed method shows the highest performance in terms of accuracy, sensitivity, specificity, f- measures, g-means, precision and recall when compared with support vector machine respectively.

6. CONCLUSION AND FUTURE WORK

The structural and textural features is explored for melanoma recognition. These features are obtained from the different variants of operator like FFT(Fast Fourier Transform), Histogram based bin separation. The obtained results are validated using KNN classifier. Melanoma is the dangerous type of skin cancer having highest mortality rate. Whereas, the annihilation in their early stage gives a high survival rate so that it demands early diagnosis. The accustomed diagnosis methods are expensive and inefficient due to the involvement of experienced experts with their requirements for the highly equipped environment. The recent advancements in the proposed system for this diagnosis are highly promising with improved accuracy and efficiency. The basic aim of this work is a simple, efficient and automatic skin cancer, detection and diagnosis system with the use of commonly available software for non- experts/clinicians/doctors. The accuracy of classification is measured and presented in the experimental results. The results revealed that the classification accuracy is influenced by the size of training set. In future more measures should be taken to evaluate the proposed methodology and improve it further to make it robust and adapt it to specific applications. A fuzzy-neural expert system can be built as a further study of the presented work to classify the Malignant Melanoma into superficial and on the basis of clinical and morphological features. Emerging technologies such as in vivo reflectance confocal microscopy are currently being investigated to determine their utility for noninvasive diagnosis of melanoma. This review summarizes the currently available cutaneous imaging devices and new frontiers in noninvasive diagnosis of skin disease. Also author anticipate that multimodal systems which combine different imaging technologies will further improve the ability to detect melanoma at an earlier stage.

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