

SKIN CANCER CLASSIFICATION USING REGION GROWING ADAPTIVE MEAN THRESHOLDING (RGAMT) AND DEEP LEARNING

Submitted in partial fulfilment of the requirements for the award
of Bachelor of Engineering Degree

in

Electronics and Communication Engineering

By

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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

SCHOOL OF ELECTRICAL AND ELECTRONICS

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this final year project Report is the bonafide work of TUNGALA SRIPATHINAIDU(39130483) and VENKAT NATAKARANI(39130508) who have done the project work as an individual who carried out the project entitled "SKIN CANCER CLASSIFICATION USING REGION ADAPTIVE MEAN THRESHOLDING (RGAMT) AND DEEP LEARNING" under my supervision from Jan 2023 to April 2023.

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We, TUNGALA SRIPATHINAIDU (39130483) and NATAKARANI VENKAT (39130508).We hereby declare that the Project Report entitled “**SKIN CANCER CLASSIFICATION USING REGION GROWING ADAPTIVE MEAN THRESHOLDING (RGAMT) AND DEEP LEARNING**” done by us under the guidance of **Dr. R Narmadha, M.E, Ph.D.,** Associate Professor is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electronics and Communication Engineer

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ABSTRACT

Skin cancer becomes common disease, physical analysis of skin cancer is highly time-taking processing and highly cost expensive. It is necessary to program computerized analysis techniques with the capability to categorize multiclass skin cancer with high efficiency and accuracy, for early diagnosis of skin cancer using demographic image and classify multiclass skin cancer by applying the most dominant features. Pre-processing of noisy low-quality image is 2D-BADSD filter is applied to eliminate all noises and 2D EP-AHCE is used to improve contrast and brightness of the image (image enhancement). Image segmentation involves image clustering Roi (region of interest) and image thresholding (to extract only Roi). The useful statistical and mathematics features are calculated on the segmented image using Gray Level Co-Occurrence Matrix (GLCM), 2D-Iterative Convolutional Neural Network (2D-ICNN) classification methodology is applied to categorize multiclass classification of skin cancer.

TABLE OF CONTENTS

CHAPTER No.	TITLE	PAGE No.
1	INTRODUCTION	
	1.1 INTRODUCTION	9
	1.2 PROBLEM STATEMENT	10
	1.3 OBJECTIVE	10
	1.4 AIM	11
	1.5 SCOPE OF THE PROJECT	11
2	LITERATURE SURVEY	
	2.1 LITERATURE REVIEW	12
3	EXISTING SYSTEM	15
	3.2 DISADVANTAGES OF EXISTING SYSTEM	15
	3.3 PROPOSED SYSTEM	16
	3.3.1 MODULE 1- RESTORATION	16
	3.3.2 MODULE 2- ENHANCEMENT	16
	3.3.3 MODULE 3- SEGMENTATION	17
	3.3.4 MODULE 4- EXTRACTION	17
	3.4 EXISTING METHODOLOGY	18
	3.5 PROPOSED METHODOLOGY	18
	3.6 DIFFERENCE B/W EXISTING AND PROPOSED METHODOLOGY	19
	3.7 BLOCK DIAGRAM	20
	3.8 ADVANTAGES FOR THE PROPOSED	20

METHODOLOGY	
3.9 IMAGE PROSSESING OVERVIEW	21
3.9.1 IMAGE RESTORATION	22
3.9.2 IMAGE ENHANCEMENT	22
3.10 INFORMATION EXTRACTION	22
3.11 CONTRST ENHANCEMENT	23
3.12 DEGRADATION MODEL	23
3.13 SKIN CANCER	26
3.14 FLOW CHART	27
3.15 IMAGE DENOISING USING 2D	
ANISOTROPIC FILTER	28
3.16 THE K-MEANS ALGORITHM	31
3.17 FUZZY CLUSTERING ALGORITHM	31
3.18 THE FAST FUZZY C-MEANS ALGORITHM	32
3.19 FUZZY C-MEANS IMPLEMENTATION	32
3.20 FEATURE EXTRACTION	33
3.21 FACTORS CONCERNING THE	
SEGMENTATION	36
3.22 MATHEMATICAL MODEL	36
3.23 TEXTURE FEATURE EXTRACTION	39
3.24 FSVM CLASSIFIER	39
3.25 LIST OF FEATURES	39
3.25.1 CONTRAST	39

	3.25.2 AUTOCORRELATION	40
	3.25.3 CROSS CORRELATION	40
	3.25.4 CLUSTER SHADE AND CLUSTER PROMINENCE	40
	3.25.5 DISSIMILARITY	40
	3.25.6 SUM OF SQUARES	41
	3.25.7 SUM OF AVERAGE	41
	3.25.8 SUM OF VARIANCE	41
	3.25.9 IMAGE ENTROPY	41
	3.26 STATISTICAL LEARNING THEORY	42
	3.27 CONVOLUTION NEURAL NETWORK CLASSIFICATION	42
	3.28 CNN FOR CLASSIFICATION	46
4	RESULTS AND DISCUATION	47
	CONCLUSION	51
	CONSTRAINT	52
	STANDARDIZATION	53
	REFERENCE	54
	RESEARCH PAPER	55

CHAPTER 1

1.1 Introduction

According to the World Health Organization (WHO), skin cancer accounts for one third of all types of cancers. Each year, skin cancer cases increase and result in a higher number of deaths. Currently, approximately 3 million non-melanoma and 132,000 melanoma skin cancer cases are diagnosed globally every year. According to the WHO, 9500 people receive a skin cancer diagnosis every day in the US alone, and two people die every hour. The average annual cost of treating such cases is USD 3.3 and 4.8, respectively. As per the statistics, the number of invasive melanoma cases has increased by 47% in the last ten years. In Europe, more than 100,000 new cases of diagnosed melanoma are reported annually. In Australia, on the other hand, the number of annual reported cases of melanoma is 15,229. However, the latest statistics show that the number of skin cancer cases has been increasing since 1990. The current trend was explained by the reducing ozone layer and the increased use of solariums and tanning beds. Skin cancer is the most common cancer in the United States and worldwide. Although the majority of the works in the literature are focused on melanoma detection, the most common malign skin lesion is the skin cancer. Over 95% of NMSC cases are Basal Cell Carcinoma (BCC) and cutaneous squamous cell carcinoma (SCC). Specifically, BCC has an incidence higher than 70% among all skin cancer, it has the best validated clinical criteria for its diagnosis, and it presents the higher variability in the presence of these dermoscopic criteria. The detection of skin disease can be performed by visual inspection by a skilled dermatologist, but there are many benign lesions that can be confused with skin disease, leading to unnecessary biopsies, in a proportion of five biopsies versus one actual cancer case. The increase in the incidence of BCC is provoking an overload for dermatologists. In the Andalusian Health System, dermatology is being implanted. Nowadays, 315 demands of tele-dermatology consultation per month are received and 210 receive diagnostic criteria of BCC. Thus, a Computer Aided Diagnosis (CAD) tool that assists general practitioner physicians and provides a prioritization in the dermatology consultation would have great utility. Different kinds of images have been traditionally used in order to classify NMSC automatically (spectroscopy, optical coherence tomography, etc.). However, the simplest one and most used is the digital dermoscopy, that is, a digital color photograph, enhanced by a dermoscope. Lately, and due to the availability of

databases due to the challenges proposed by ISIC, the use of artificial intelligence methods, and in particular, the use of deep learning neural networks, have become very popular in dermatology.

1.2 PROBLEM STATEMENT

Skin cancer (melanoma and non-melanoma) is one of the most common cancer types and leads to hundreds of thousands of yearly deaths worldwide. It manifests itself through abnormal growth of skin cells. Early diagnosis drastically increases the chances of recovery. Moreover, it may render surgical, radiographic, or chemical therapies unnecessary or lessen their overall usage. Thus, healthcare costs can be reduced. The process of diagnosing skin cancer starts with dermo copy, which inspects the general shape, size, and color characteristics of skin lesions, and suspected lesions undergo further sampling and lab tests for confirmation. Image-based diagnosis has undergone great advances recently due to the rise of deep learning artificial intelligence. The work in this paper examines the applicability of raw deep transfer learning in classifying images of skin lesions into six possible categories.

1.3 Objective

The objective of this project is to provide an efficient way to segment the skin cancer images. A novel method is proposed that combines color and texture for the segmentation of skin lesions from unaffected skin region in an image. The distributions of color and texture features provide a good discrimination of skin lesions. The segmentation results will be evaluated quantitatively by means of a comparative experiment on a set of skin cancer images.

- Skin Image Filtering
- Skin Image Enhancement
- Skin Image Clustering
- Skin Image Thresholding
- Feature Extraction
- Classification using Deep Learning (DL)

1.4 AIM

Now a days the application of image processing and segmentation plays an important role in medical analysis. The cancer has found to be the most common and hazardous disease. Skin cancer may be of different types like Melanoma, Basal cell among which Melanoma is the most dangerous, uncertain and unpredictable. Detection of skin cancer in the earlier stage is important and can be helpful to cure it. The automated MATLAB tool has to be developed to detect the skin cancer and lesion on digital images.

1.5 Scope of the project

To analyze skin lesions, it is necessary to accurately locate and isolate the lesions. The description of the border aspect appears to be an important feature for clinical judgment. The variation in color signifies the malignancy of the lesion. Hence effective discrimination of the skin lesions was based on the distribution of texture and color features in this project. A pre-processing step was adopted to remove the influence of skin lesions in the surrounding regions and also the influence of small structures, hairs, bubbles etc.

CHAPTER 2

2.1 LITERATURE REVIEW

S. Jiang, H. Li and Z. Jin, "A Visually Interpretable Deep Learning Framework for Histopathological Image-Based Skin Cancer Diagnosis," Owing to the high incidence rate and the severe impact of skin cancer, the precise diagnosis of malignant skin tumors is a significant goal, especially considering treatment is normally effective if the tumor is detected early. Limited published histopathological image sets and the lack of an intuitive correspondence between the features of lesion areas and a certain type of skin cancer pose a challenge to the establishment of high-quality and interpretable computer-aided diagnostic (CAD) systems. To solve this problem, a light-weight attention mechanism based deep learning framework, namely, DRANet, is proposed to differentiate 11 types of skin diseases based on a real histopathological image set collected by us during the last 10 years. The CAD system can output not only the name of a certain disease but also a visualized diagnostic report showing possible areas related to the disease.

S. Back et al., "Robust Skin Disease Classification by Distilling Deep Neural Network Ensemble for the Mobile Diagnosis of Herpes Zoster Herpes zoster (HZ) is a common cutaneous disease affecting one out of five people; hence, early diagnosis of HZ is crucial as it can progress to chronic pain syndrome if antiviral treatment is not provided within 72 hr. Mobile diagnosis of HZ with the assistance of artificial intelligence can prevent neuropathic pain while reducing clinicians' fatigue and diagnosis cost. However, the clinical images captured from daily mobile devices likely contain visual corruptions, such as motion blur and noise, which can easily mislead the automated system. Hence, this paper aims to train a robust and mobile deep neural network (DNN) that can distinguish HZ from other skin diseases using user-submitted images. To enhance robustness while retaining low computational cost, a knowledge distillation is proposed from ensemble via curriculum training (KDE-CT) wherein a student network learns from a stronger teacher network progressively. Skin diseases dataset for HZ diagnosis and evaluated the robustness against 75 types of corruption. A total of 13 different DNNs was evaluated on both clean and corrupted images. The experiment result shows that the proposed KDE-CT significantly improves corruption robustness when compared with other methods. Our

trained MobileNetV3-Small achieved more robust performance (93.5% overall accuracy, 67.6 mean corruption error) than the DNN ensemble with smaller computation (549x fewer multiply-and-accumulate operations), which makes it suitable for mobile skin lesion analysis.

N. C. Lynn and Z. M. Kyu, "Segmentation and Classification of Skin Cancer Melanoma from Skin Lesion Images," 2017 18th International Conference on Parallel and Distributed Computing, Applications and Technologies To minimize the diagnostic error caused by the complexity of visual interpretation and subjectivity, it is important to develop a technology for computerized image analysis. This paper presents a methodological approach for the classification of pigmented skin lesions in dermoscopic images. Firstly, the image of the skin to remove unwanted hair and noise, and then the segmentation process is performed to extract the affected area. For detecting the melanoma skin cancer, the mean shift algorithm that segments the lesion from the entire image is used in this study. Feature extraction is then performed by underlying ABCD dermatology rules. After extracting the features from the lesion, feature selection algorithm has been used to get optimized features in order to feed for classification stage. Those selected optimized features are classified using kNN, decision tree and SVM classifiers. The performance of the system was tested and compare those accuracies and get promising results.

L. Li and W. Seo, "Deep Learning and Transfer Learning for Skin Cancer Segmentation and Classification," 2021 IEEE 21st International Conference on Bioinformatics and Bioengineering (BIBE) According to Skin Cancer Foundation, skin cancer is by far the most common type of cancer in the United States and worldwide. Early diagnosis of skin cancer is critical because proper treatment at early stages can increase the chance of cure and recovery. However, visual inspection of dermoscopic images by dermatologists is error-prone and time-consuming. To ensure accurate diagnosis and faster treatment of skin cancer, deep learning techniques have been utilized to conduct automated skin lesion segmentation and classification. In this paper, after image processing, a Mask R-CNN model is built for lesion segmentation, where transfer learning is utilized by using the pre-trained weights from Microsoft COCO dataset. The weights of the trained Mask R-CNN model are saved and transferred to the next task - skin lesion classification, to train a Mask R-CNN model for classification. Our experiments are conducted on the benchmark datasets from the International Skin Imaging Collaboration 2018 (ISIC 2018) and evaluated by the same metrics used in ISIC 2018. The

lesion boundary segmentation and lesion classification have achieved an accuracy of 96% and a balanced multiclass accuracy of 80%, respectively.

S. Das and D. Das, "Skin Lesion Segmentation and Classification: A Deep Learning and Markovian Approach," 2021 IEEE Mysore Sub Section International Conference (MysuruCon), Skin cancer is a very dangerous type of cancer which can spread in other organs if not detected early. Skin Melanoma is a type of cancer where melanocytes mutate rapidly. It is estimated that 99% of people can survive this type of cancer if it is detected at an early stage. A feedforward neural network with fully connected dense layers and Gray Level Co-occurrence Matrix as features is used which gives an AUC score of 0.63 on the private leader board of SIIM ISIC 2020 challenge. A pre-trained EfficientNETB7 is used to achieve an AUC score of 0.73 after the images from the SIIM ISIC challenge was augmented with ISIC 2019 challenge images. Segmentation of the skin cancer images from PH2 dataset is done using Markov Random Field, An Encoder-Decoder network is proposed to segment the images in the PH2 dataset. A precision of 0.91 and a dice coefficient of 0.73 are achieved on the validation dataset using the Encoder-Decoder network. Segmentation can be followed by feature extraction of the lesions and then classification can be performed using machine learning.

M. S. Manerkar, U. Snehalatha, S. Harsh, J. Saxena, S. P. Sarma and M. Anburajan, "Automated skin disease segmentation and classification using multi-class SVM classifier," 3rd International Conference on Electrical, Electronics, Engineering Trends, Communication, Optimization and Sciences The aim and objectives of the study is to perform automated segmentation of different skin cancer images using C-means and watershed algorithm and features extraction by Gray Level Co-occurrence Matrix (GLCM) and Image Quality Assessment (IQA) method. In the Proposed method, 45 digital images collected from MIT BMI database consists of warts, benign skin cancer and malignant skin cancer and normal skin images. Then these images are segmented using c-means and watershed algorithms individually. Feature extraction is performed using GLCM and IQA methods for examining texture which gave the statistical parameters of each algorithm respectively. In this work, different types of skin diseases are commonly classified as Benign Skin Cancer, Malignant Skin Cancer and Warts using multi-class SVM (Support Vector Machine).

CHAPTER 3

3.1 Existing system

Texture distinctiveness lesion segmentation (TDLS) algorithm

TDLS algorithm is simple. However, it is easy to get stuck in local optimal with error pixel extraction. The algorithm tends to get stuck less than K-means algorithm. The idea is to assign data points partially to different clusters instead of assigning to only one cluster. To do this partial assignment, we model each cluster using a probabilistic distribution. So a data point associates with a cluster with certain probability and it belongs to the cluster with the highest probability in the final assignment. We can use mixture of Gaussian distributions to model this. The mixture model is a weighted sum of K Gaussian distributions.

3.2 DISADVANTAGES OF EXISTING SYSTEM

- The region growing segmentation (TDLS) is not preferred for its limited range of applications and automatic features are not having accurate values.
- Preprocessing experiments are needed to find which type of filtering will be more beneficial. This increases the effect of the speckle noise and Gaussian noise the ultrasound, mammogram Images and MRI Images.
- The desired cancer area is selected from the segmented image to calculate the volume. The volume of the desired cancer area is greater than the original cancer area. The region growing algorithm will segment not only the tumor area but also the non-tumor area which has high intensity ratio.
- This algorithm fully depends on the intensity of the image not the shape and texture. So the accuracy and sensitivity is low.

3.3 Proposed System

1. Image Restoration – Anisotropic Diffusion Filter (PSNR will be high)
2. Image Enhancement – Adaptive Mean Adjustment
3. Image Segmentation – FAST FUZZY C MEANS (FFCM)
4. Feature Extraction – Gray Level Co-occurrence Matrix (GLCM), Band-let Transform.
5. Classification – Convolution Neural Network

3.3.1 Module 1

Image Restoration – Anisotropic Diffusion Filter

The simplest and best investigated diffusion method for smoothing images is to apply a linear diffusion process. We shall focus on the relation between linear diffusion filtering and the convolution with a Gaussian, analyze its smoothing properties for the image as well as its derivatives, and review the fundamental properties of the Gaussian scale-space induced by linear diffusion filtering.

3.3.2 Module 2

Image Enhancement – Adaptive Mean Adjustment (AMA)

AMA is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast of an image and bringing out more detail.

However, AHE has a tendency to over-amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called AMA algorithm prevents this by limiting the amplification

3.3.3 Module 3

Image Segmentation – FAST FUZZY C MEANS (FFCM)

In this module FAST FUZZY C MEANS (FFCM) segmentation algorithm will be implemented to overcome the problem of existing system skin lesion and cancer segmentation mishandling by initializing standard membership values (computed by template averaging) so that standard segmentation result for each and every image was obtained. The number of clusters, initial standard intensity values and the feature vector were given as the input. After the completion of initial clustering process, the clusters were updated in turn updates the cluster weights and membership degree. An objective function will determine that up to which the clusters should be updated.

3.3.4 Module 4

Feature Extraction – Gray Level Co-occurrence Matrix (GLCM), Band-let Transform

The Following GLCM features were extracted in our research work: Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity Energy, Entropy, Homogeneity, Maximum probability, Sum of squares, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation, information measure of correlation, Inverse difference normalized. The 2D band-let transform is used to convert the spatial domain skin image into frequency domain image to estimate real and imaginary part of the image.

Classification – Convolution Neural Network

Convolution Neural Network (CNN) is commonly known as neural network which is a mathematical motivated by the structure of biological neural networks. A neural network consists of an interconnected group of artificial neurons. This work describes the use of neural network in classification of medical images such as skin cancer and lesion , where the input units represents the feature vector and the output units represents the pattern class which has to

be classify. Each input vector (feature vector) is given to the input layer, and output of each unit is corresponding element in the vector. Each hidden units calculates the weighted sum of its input to outline its scalar a net activation. The product of input vector and weight matrix at the hidden layer is generally called net activation function. Convolution Neural network is a useful tool for skin cancer classification. The advantage of parallel processing in deep learning and their ability to classify the data based on features provides a promising platform for medical image classification. Traditional sequential processing techniques have limitations for implementing pattern recognition problems in terms of flexibility and cost whereas back propagation neural networks perform the processing task by training the features calculated from the training signals instead of programming in a manner similar to the way human brain learns. The CNN works based on the trained features fed to the hidden layer of the neural network through the training sequence. The various features are calculated and fed to the hidden layer through the sigmoid function based on the weight vector generated by the input layer of the CNN.

3.4 Existing Methodology

Melanoma skin cancer is one of the most dangerous types of skin cancer, which, if not diagnosed early, may lead to death. Therefore, an accurate diagnosis is needed to detect melanoma. Traditionally, a dermatologist utilizes a microscope to inspect and then provide a report on a biopsy for diagnosis; however, this diagnosis process is not easy and requires experience. Hence, there is a need to facilitate the diagnosis process while still yielding an accurate diagnosis. For this purpose, artificial intelligence techniques can assist the dermatologist in carrying out diagnosis.

3.5 Proposed Methodology

Image Filtering - 2-Dimensional Bilateral Anisotropic Diffusion Spatial Domain (2D-BADSD)

Image Enhancement - 2D-Edge Preservation-Adaptive Histogram and Coherence Equalization (2D EP-AHCE).

Image segmentation - Region Growing Adaptive Mean Thresholding (RGAMT).

The image clustering algorithm is used to cluster the Region of Interest (ROI) pixels, i.e., skin cancer region pixels and Non-Region of Interest (NROI) pixels, i.e., non-cancer region pixels.

Image thresholding technique is applied to extract only ROI and suppress NROI.

Feature Extraction - Gray Level Co-Occurrence Matrix (GLCM).

Skin cancer classification - 2D-Deep Convolutional Neural Network (2D-ICNN) classification

3.6 Difference between Existing and proposed methodology

An increasing number of genetic and metabolic anomalies have been determined to lead to cancer, generally fatal. Cancerous cells may spread to any body part, where they can be life-threatening. Skin cancer is one of the most common types of cancer, and its frequency is increasing worldwide. The main subtypes of skin cancer are squamous and basal cell carcinomas, and melanoma, which is clinically aggressive and responsible for most deaths. Therefore, skin cancer screening is necessary. One of the best methods to accurately and swiftly identify skin cancer is using deep learning (DL). In this research, the deep learning method convolution neural network (CNN) was used to detect the two primary types of tumors, malignant and benign, using the ISIC2018 dataset. This dataset comprises 3533 skin lesions, including benign, malignant, nonmelanocytic, and melanocytic tumors. Clinical treatment of skin lesion is primarily dependent on timely detection and delimitation of lesion boundaries for accurate cancerous region localization. Prevalence of skin cancer is on the higher side, especially that of melanoma, which is aggressive in nature due to its high metastasis rate. Therefore, timely diagnosis is critical for its treatment before the onset of malignancy. To address this problem, medical imaging is used for the analysis and segmentation of lesion boundaries from dermoscopic images. Various methods have been used, ranging from visual inspection to the textural analysis of the images. However, accuracy of these methods is low for proper clinical treatment because of the sensitivity involved in surgical procedures or drug application. This presents an opportunity to develop an automated model with good accuracy so that it may be used in a clinical setting.

3.7 BLOCK DIAGRAM

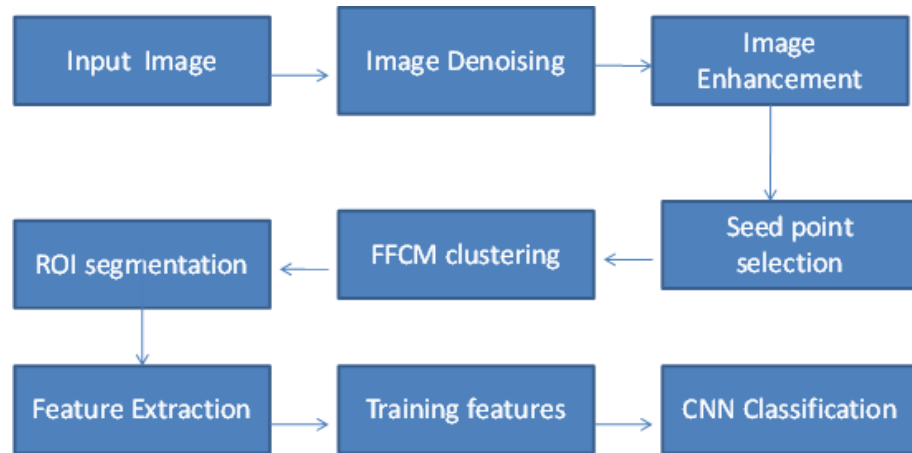


Fig: 1 : block diagram

3.8 Advantages for the proposed methodology

In this segmentation algorithm will be implemented to overcome the problem of existing system skin lesion and cancer segmentation mishandling by initializing standard membership values (computed by template averaging) so that standard segmentation result for each and every image was obtained. The number of clusters, initial standard intensity values and the feature vector were given as the input. After the completion of initial clustering process, the clusters were updated in turn updates the cluster weights and membership degree. An objective function will determine that up to which the clusters should be updated.

The Following GLCM features were extracted in our research work: Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity Energy, Entropy, Homogeneity, Maximum probability , Sum of squares, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation, information measure of correlation, Inverse difference normalized. The 2D band-let transform is used to convert the spatial domain skin image into frequency domain image to estimate real and imaginary part of the image.

3.9 IMAGE-PROCESSING OVERVIEW

Digital Image Processing (DIP) involves the modification of digital data for improving the image qualities with the aid of computer. The processing helps in maximising clarity, sharpness and details of features of interest towards information extraction and further analysis. This form of remote sensing actually began in 1960s with a limited number of researchers analysing airborne multispectral scanner data and digitised aerial photographs. However, it was not until the launch. Digital image data became widely available for land remote sensing applications. At that time not only the theory and practice of digital image processing was in its infancy but also the cost of digital computers was very high and their computational efficiency was far below by present standards. Today, access to low cost and efficient computer hardware and software is commonplace and the source of digital image data are many and varied. The digital image sources range from commercial earth resources satellites, airborne scanner, airborne solid-state camera, scanning micro-densitometer to high-resolution video camera. Digital image processing is a broad subject and often involves procedures which can be mathematically complex, but central idea behind digital image processing is quite simple. The digital image is fed into a computer and computer is programmed to manipulate these data using an equation, or series of equations and then store the results of the computation for each pixel (picture element).

These results form a new digital image that may be displayed or recorded in pictorial format or may itself be further manipulated by additional computer programs. The possible forms of the digital image manipulation are literally infinite. To selectively enhance certain fine features in the data and to remove certain noise, the digital data is subjected to various image processing operations. Image-processing methods may be grouped into three functional categories:

These are defined below together with lists of typical processing techniques.

3.9.1 IMAGE RESTORATION

Image Restoration compensates for data errors, noise and geometric distortions introduced during the scanning, recording, and playback operations.

- a. Restoring periodic line dropouts
- b. Restoring periodic line striping
- c. Filtering of random noise
- d. Correcting for atmospheric scattering
- e. correcting geometric distortions

3.9.2 IMAGE ENHANCEMENT

Image Enhancement alters the visual impact that the image has on the interpreter in a fashion that improves the information content.

- a. Contrast enhancement
- b. Intensity, hue, and saturation transformations
- c. Density slicing
- d. Edge enhancement
- e. Making digital mosaics
- f. Producing synthetic stereo image

3.10 INFORMATION EXTRACTION

Information Extraction utilizes the decision-making capability of the computer to recognize and classify pixels on the basis of their digital signatures,

- a. Producing principal-component images
- b. Producing ratio images
- c. Multispectral classification
- d. Producing change-detection images

Enhancement is the modification of an image to alter impact on the viewer. Generally enhancement distorts the original digital values; therefore enhancement is not done until the restoration processes are completed.

3.11 Contrast Enhancement

There is a strong influence of contrast ratio on resolving power and detection capability of images. Techniques for improving image contrast are among the most widely used enhancement processes. The sensitivity range of any remote sensing detector is designed to record a wide range of terrain brightness from black basalt plateaus to white sea beds under a wide range of lighting conditions.

Few individual scenes have a brightness range that utilizes the full sensitivity range of these detectors. To produce an image with the optimum contrast ratio, it is important to utilize the entire brightness range of the display medium, which is generally film. The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. Degradation comes in many forms such as motion blur, noise, and camera misfocus. In cases like motion blur, it is possible to come up with a very good estimate of the actual blurring function and "undo" the blur to restore the original image. In cases where the image is corrupted by noise, the best we may hope to do is to compensate for the degradation it caused.

In this project, we will introduce and implement several of the methods used in the image processing world to restore images.

3.12 Degradation Model

The block diagram for our general degradation model is

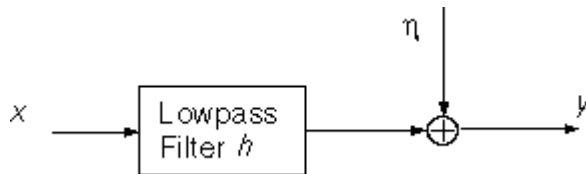


Fig: 2 : General degradation model

where g is the corrupted image obtained by passing the original image f through a low pass filter (blurring function) b and adding noise to it.

To understand what adaptive median filtering is all about, one first needs to understand what a median filter is and what it does. In many different kinds of digital image processing,

the basic operation is as follows: at each pixel in a digital image we place a neighborhood around that point, analyze the values of all the pixels in the neighborhood according to some algorithm, and then replace the original pixel's value with one based on the analysis performed on the pixels in the neighborhood. The neighborhood then moves successively over every pixel in the image, repeating the process. The MRI algorithm first classifies the pixels of a localized window, centering on the current pixel, into three groups lower intensity impulse noise, uncorrupted pixels, and higher intensity impulse noise. The center pixel will then be considered as uncorrupted, provided that it belongs to the uncorrupted pixel group, or corrupted. For that, two boundaries that discriminate these three groups require to be accurately determined for yielding very high noise detection accuracy. The MRI algorithm is applied to each pixel of the noisy image in order to identify whether it is uncorrupted or corrupted. After such an application to the entire image, a two-dimensional binary decision map is formed at the end of the noise detection stage, with 0s indicating the positions of uncorrupted pixels, and 1s for those corrupted ones.

To accomplish this objective, all the pixels within a pre-defined window that center on the considered pixel will be grouped into three clusters; hence, two boundaries b_1 and b_2 are required to be determined. For each pixel being considered, if $0 \leq x_{i,j} \leq b_1$, the pixel will be assigned to the lower-intensity cluster; otherwise, to the medium-intensity cluster for $b_1 < x_{i,j} \leq b_2$ or to the high-intensity cluster for $b_2 < x_{i,j} \leq 255$. Obviously, if the center pixel being considered falls onto the middle cluster, it will be treated as uncorrupted, since its intensity value is neither relatively low nor relatively high. Otherwise, it is very likely that the pixel has been corrupted by impulse noise. Clearly, the accuracy of clustering results (hence, the accuracy of noise detection) ultimately depends on how accurate the identified boundaries b_1 and b_2 .

The boundary discriminative process consists of two iterations, in which the second iteration will only be invoked conditionally. In the first iteration, an enlarged local window with a size of 21×21 (empirically determined) is used to examine whether the considered pixel is an uncorrupted one.

Noise is any undesired information that contaminates an image. Impulse noise is a special type of noise, which have many different origins.

The Salt and Pepper type impulse noise is typically caused by malfunctioning of the pixel elements in the camera sensors, faulty memory locations, or timing errors in the

digitization process. For the images corrupted by Salt and Pepper noise, the noisy pixels can take only the maximum or the minimum values in the dynamic range.

An important non linear filter that will preserve the edges and remove impulse noise is standard median filter Median (SMF). It replaces every pixel by its median value from its neighborhood and often removes desirable details in the image.

Specialized median filter such as weighted median filter (WMF) were proposed to improve the performance of median filter by giving more weight to some selected pixel in the filtering window. Some of decision based algorithms, such as Adaptive Median filter (AMF), These algorithms first detect the noisy pixels and remove it by applying either standard median filter or its variants. These filters are effective in removing low to medium density impulse noise only.

1. Less effective in removing Gaussian or random-intensity noise. The median filter can remove noise only if the noisy pixels occupy less than one half of the neighborhood area.
2. Repeating will remove noise but at the expense of detail (occurs) where pixel brightness values are leveled across regions "group of pixels having similar brightness values
3. High computational cost (for sorting N pixels, the temporal complexity is $O(N \cdot \log N)$, When the median filter must be carried out in real time, the software implementation in general-purpose processors does not usually give good results and a good alternative.
4. Some median algorithms are not good for real time processing.
5. The median filter gives brightness differences resulting in maximal blurring of regional boundaries.

3.13 SKIN CANCER

Cancer is one of the biggest threats to human beings and is the second leading cause of death the entire world human. According to the statistical data from WHO(World Health Organization), cancer caused about 7.6 million people death worldwide in 2008, and it is predicted that the number of deaths caused by cancer is being increased and the number will possibly increase to 13.1 million in 2030. Based on related research, cancer will become the leading death in next 20 years. There are three types of skin cancer: Basal cell cancer and squamous cell cancer are called non-melanoma skin cancer while melanoma is on melanocytes cells, Basal cell cancer and squamous cell cancer are common but less dangerous. Melanoma is not common as non-melanoma skin cancers, however, it is more likely to spread and become fatal Although skin cancer is a threat to human life, fortunately even melanoma can be cured if it is detected early. According to research, the curable rate will be more than 90% high if cancer can be diagnosed in its early stages while the curable rate will be less than 50% in its late stage. Thus, the detection of skin cancer in its early stage has attracted the attention from different fields Currently the diagnosis of skin cancer is done mainly by a human, who is called dermatologist. During diagnosis, a dermatologist exam the skin carefully by his eyes or using a device called derma scope. During this stage, dermatologists generally use “ABCD” rule to find the signs of skin cancer. ABCD means Asymmetry, Borders (irregular), Color (variegated), Diameter (greater than 6mm) of a skin patch. By observing the early signs using “ABCD” rule, dermatologists can classify whether a skin patch is benign or malignant. If a patch is determined to be malignant, a biopsy will be used to confirm the final result. Although the procedure used above is standard, a dermatologist has subjective bias and the correct diagnosis depends on a dermatologist's experience. Besides, the procedure examined by a dermatologist takes long time. In order to improve the diagnosis rate, computer aided skin cancer detection techniques have been investigated to aid the dermatologists for skin cancer detection. The basic idea of computer-aided detection (CAD) is to use imaging technique, image processing technique, and pattern recognition technique to detect the suspected skin patches. It is used generally as the second opinion to a dermatologist.

In MATLAB, **image segmentation** is the process of partitioning a digital **image** into multiple segments (sets of pixels, also known as super pixels). The goal of **segmentation** is to simplify

and/or change the representation of an **image** into something that is more meaningful and easier to analyze.

Segmentation partitions an image into distinct regions containing each pixel with similar attributes. To be meaningful and useful for image analysis and interpretation, the regions should strongly relate to depicted objects or features of interest. Meaningful segmentation is the first step from low-level image processing transforming a greyscale or colour image into one or more other images to high-level image description in terms of features, objects, and scenes. The success of image analysis depends on reliability of segmentation, but an accurate partitioning of an image is generally a very challenging problem.

Segmentation techniques are either contextual or non-contextual. The latter take no account of spatial relationships between features in an image and group pixels together on the basis of some global attribute, e.g., grey level or colour. Contextual techniques additionally exploit these relationships, e.g., group together pixels with similar grey levels and close spatial locations.

3.14 FLOW CHART

Input Image →

Preprocessing

Image Denoising using 2D anisotropic Filter →

Segmentation

Calculate the Centroid Pixel from the image using K means algorithm →

Calculate the foreground and background pixels using morphological operation →

Apply the Fast Fuzzy C Means (FFCM)for segmenting the cancer pixels →

Feature extraction →

Classification →

Decision Making (Normal or abnormal) →

Accuracy Calculation

3.15 Image Denoising using 2D anisotropic Filter

2D anisotropic diffusion follows this basic prescription. The **2D anisotropic diffusion** is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. This class of filter belongs to the class of edge preserving smoothing filters which are non-linear filters. This means that for two images $A(x)$ and $B(x)$:

$$\textit{median}[A(x) + B(x)] \neq \textit{median}[A(x)] + \textit{median}[B(x)]$$

These filters smooth the data while keeping the small and sharp details. The median is just the middle value of all the values of the pixels in the neighborhood. Note that this is not the same as the average (or mean); instead, the median has half the values in the neighborhood larger and half smaller. The median is a stronger "central indicator" than the average. In particular, the median is hardly affected by a small number of discrepant values among the pixels in the neighborhood. Consequently, **2D anisotropic diffusion** filtering is very effective at removing various kinds of noise. Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. The morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to grey-scale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighborhoods of pixels. Some operations test whether the element "fits" within the neighborhood, while others test whether it "hits" or intersects the neighbourhood:

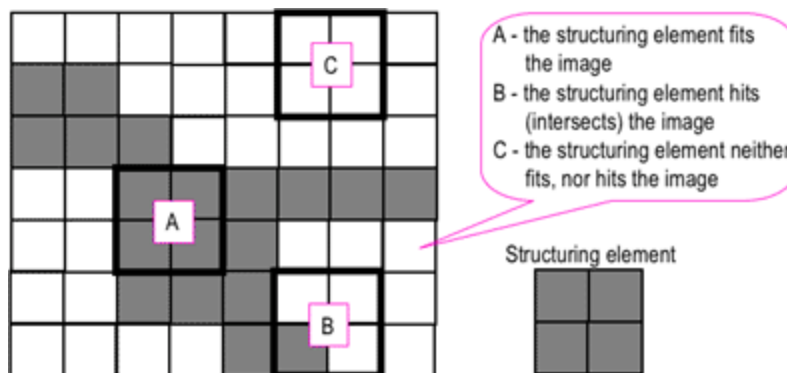


Fig: 3 :morphological

A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image.

The structuring element is a small binary image, i.e. a small matrix of pixels, each with a value of zero or one:

- The matrix dimensions specify the size of the structuring element.
- The pattern of ones and zeros specifies the shape of the structuring element.
- An origin of the structuring element is usually one of its pixels, although generally the origin can be outside the structuring element.

A common practice is to have odd dimensions of the structuring matrix and the origin defined as the Centre of the matrix. Structuring elements play in morphological image processing the same role as convolution kernels in linear image filtering.

When a structuring element is placed in a binary image, each of its pixels is associated with the corresponding pixel of the neighbourhood under the structuring element. The

structuring element is said to **fit** the image if, for each of its pixels set to 1, the corresponding image pixel is also 1. Similarly, a structuring element is said to **hit**, or intersect, an image if, at least for one of its pixels set to 1 the corresponding image pixel is also 1.

Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant.

Skin Cancer Segmentation

Image Clustering Techniques

K Means algorithm

1. Digitize the image and get the pixel values.
2. Convert into double precision in order to increase the memory.
3. Calculate the normalized histogram.

The normalized histogram is used to calculate the clustering values for AMS EM algorithm. That decides the K value for the clustering.

4. Calculate the mean value for the normalized image.
5. Calculate the expectation pixels.

(Expectation pixels are called the unusual pixels which have unusual intensity. These pixels are calculated throughout the image and considered as expected pixel intensity).

6. Then calculate the maximization process, maximizing the expected pixel intensity and filtering the usual pixel intensity. This process is done by estimating the average of the expectation pixels and subtracting the average pixel intensity from the normalized pixels intensity.

7. Apply the thresholding value to the expectation maximization image in order to calculate the binary image.
8. Calculate the maxima from the thresholded image.
9. Reconstruct only the maxima pixels from the thresholded image.

3.16 The k-means Algorithm

The k-means algorithm assigns feature vectors to clusters by the minimum distance assignment principle, which assigns a new feature vector $\mathbf{x}^{(q)}$ to the cluster $\mathbf{c}^{(k)}$ such that the distance from $\mathbf{x}^{(q)}$ to the center of $\mathbf{c}^{(k)}$ is the minimum over all K clusters. The basic k-means algorithm is as follows:

- Put the first K feature vectors as initial centers
- Assign each sample vector to the cluster with minimum distance assignment principle.
- Compute new average as new center for each cluster
- If any center has changed, then go to step 2, else terminate.
- The advantages of the method are its simplicity, efficiency, and self-organization. It is used as initial process in many other algorithms. The disadvantages are: 1) K must be provided; 2) it is a linearly separating algorithm.

3.17 Fuzzy Clustering Algorithms

Fuzzy clustering plays an important role in solving problems in the areas of pattern recognition and fuzzy model identification. A variety of fuzzy clustering methods have been proposed and most of them are based upon distance criteria. One widely used algorithm is the fuzzy c-means (FCM) algorithm. It uses reciprocal distance to compute fuzzy weights. A more efficient algorithm is the new FCFM. It computes the cluster center using Gaussian weights, uses large initial prototypes, and adds processes of eliminating, clustering and merging. In the following sections we discuss and compare the FCM algorithm and FCFM algorithm.

3.18 The Fast Fuzzy c-means Algorithm

The fast fuzzy c-means (FFCM) algorithm was introduced. The idea of FFCM is using the weights that minimize the total weighted mean-square error:

$$J(\mathbf{w}_{qk}, \mathbf{z}^{(k)}) = \sum_{(k=1,K)} \sum_{(k=1,K)} (\mathbf{w}_{qk}) \|\mathbf{x}^{(q)} - \mathbf{z}^{(k)}\|^2 \quad (3)$$

$$\sum_{(k=1,K)} (\mathbf{w}_{qk}) = 1 \text{ for each } q$$

$$\mathbf{w}_{qk} = (1/(\mathbf{D}_{qk})^2)^{1/(p-1)} / \sum_{(k=1,K)} (1/(\mathbf{D}_{qk})^2)^{1/(p-1)}, p > 1 \quad (4)$$

The FCM allows each feature vector to belong to every cluster with a fuzzy truth value (between 0 and 1), which is computed using Equation (4). The algorithm assigns a feature vector to a cluster according to the maximum weight of the feature vector over all clusters.

3.19 Fuzzy c-means Implementation

Initialize the Fuzzy Weights. In order to comparing the FFCM with FCM, our implementation allows the user to choose initializing the weights using feature vectors or randomly. The process of initializing the weights using feature vectors assigns the first K_{init} (user-given) feature vectors to prototypes then computes the weights by Equation (4).

Standardize the Weights over Q. During the FCM iteration, the computed cluster centers get closer and closer. To avoid the rapid convergence and always grouping into one cluster, we use

$$w[q,k] = (w[q,k] - w_{min}) / (w_{max} - w_{min}) \quad (5)$$

before standardizing the weights over Q. Where w_{max} , w_{min} are maximum or minimum weights over the weights of all feature vectors for the particular class prototype.

Eliminating Empty Clusters. After the fuzzy clustering loop we add a step (Step 8) to eliminate the empty clusters. This step is put outside the fuzzy clustering loop and before calculation of modified XB validity. Without the elimination, the minimum distance of prototype pair used in Equation (8) may be the distance of empty cluster pair. We call the method of eliminating small clusters by passing 0 to the process so it will only eliminate the empty clusters.

Modified XB. After the fuzzy c-means iteration, for the purpose of comparison and to pick the optimal result, we add Step 9 to calculate the cluster centers and the modified Xie-Beni clustering validity κ :

The Xie-Beni validity is a product of compactness and separation measures. The compactness-to-separation ratio v is defined by Equation (6).

$$v = \{(1/K) \sum_{(k=1,K)} \sigma_k^2\} / D_{\min}^2 \quad (6)$$

$$\sigma_k^2 = \sum_{(q=1,Q)} w_{qk} \| \mathbf{x}^{(q)} - \mathbf{c}^{(k)} \|^2 \quad (7)$$

$D_{\min}$ is the minimum distance between the cluster centers.

The Modified Doushou validity κ is defined as

$$\kappa = D_{\min}^2 / \{ \sum_{(k=1,K)} \sigma_k^2 \} \quad (8)$$

The variance of each cluster is calculated by summing over only the members of each cluster rather than over all Q for each cluster, which contrasts with the original Doushou validity measure.

$$\sigma_k^2 = \sum_{\{q: q \text{ is in cluster } k\}} w_{qk} \| \mathbf{x}^{(q)} - \mathbf{c}^{(k)} \|^2 \quad (9)$$

3.20 FEATURE EXTRACTION

Skin cancer is the most prevalent form of human cancer. Over exposure to sun is the cause of skin cancer. Skin cancer is a malignant tumor of the skin. There are different types of skin cancer and some are likely to be fatal. Skin cancers can be classified into melanoma and non-melanoma. Melanoma is a malignancy of the cells which give the skin its colour (melanocytes). The two most frequent types of non-melanoma skin cancer are Basal Cell Carcinomas and Squamous Cell Carcinoma. In addition, there are a number of other less common skin cancers including Merkel cell tumors, cutaneous lymphomas, and sarcomas.

Melanoma is the most dangerous form of skin cancer. It can spread through the whole body and is usually fatal if it does. If detected early, the cure rate for melanoma is almost 100 percent. Late detection, when the melanoma is more than three millimeters deep, results in only a 59 percent survival rate. Melanoma's are much less common than non-melanoma's, but they account for most of the mortality from skin cancers.



Figure: 4 :Different types of Skin Cancer: (a) diameter (b) color(c) border (d) asymmetry

Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality. Early detection also saves hundreds of millions of money that is spent on the advanced disease. People are considered more at risk if they have lots of moles, are fair skinned with blue eyes, tend to sunburn easily or have freckles. The rate of melanoma cases worldwide is increasing faster than any other cancer, with an annualized rate of increase of six percent. While in the thirties of the century one out of hundred thousand people living in the United States or Europe suffered from melanoma. This number has risen to fifteen out of hundred thousand nowadays with the tendency still increasing.

Clinical features of pigmented lesions suggestive of skin cancer are known as the ABCD's of the skin cancer:

- Asymmetry
- Border irregularity
- Colour variation
- Diameter greater than 6mm

There are various image analysis techniques developed to measure these features. During the last years, a significant improvement in early tumor recognition has been achieved by using the epiluminescence microscopy (ELM). This technique uses oil immersion to render the epidermis translucent thus giving insight into subsurface structures of the skin which are not visible otherwise. This delivers a set of new features which have turned out to improve the reliability of early diagnosis considerably. The ELM criteria used by dermatologist for the classification of pigmented skin lesions are briefly outlined as follows:

- Pigmentation - Asymmetry of pigmentation is indicative of malignant lesion.
- De-pigmentation - Represents absence or diminution of pigment within a pigmented lesion.
In benign lesions, de-pigmentation is regular and usually found at the center, whereas in malignant lesions it is irregular located anywhere in the lesion and found at the periphery.
- Colour - Irregular bluish or grey-blue areas can almost exclusively be found in malignant lesions.
- Brown Globules in benign lesions - They are uniform in size and shape and regularly distributed, whereas variations in size and shape and irregular distribution indicate malignancy.
- Black Dots - When present in benign lesions, they only occur at the center and are regular in size, shape and distribution. In malignant lesions they also occur at the periphery, vary in size and shape, and are irregularly distributed.

Measurement of image features for diagnosis of the skin cancer requires the detection of lesions and localization in an image. It is essential to determine the lesion boundaries accurately so that measurements such as maximum diameter, irregularity of the boundary, and colour characteristics can be accurately computed. As a first step in skin cancer identification, the lesion boundaries are delineated by various image segmentation techniques. In this research work, colour and texture information from an image is used for the segmentation of lesion boundaries. The distributions of the texture and the distributions of the colour discriminated the colour texture image. The segmentation helps to diagnose the skin lesions in the early stages. The skin cancer images obtained from references are in graphics interchange format (gif). They were

converted to bitmap format to apply the segmentation procedure. Fifteen skin cancer images were considered for the application database.

3.21 Factors Concerning the Segmentation

Various factors that affect the segmentation of skin cancer images are as follows:

- The skin lesions have complex structure, large variations in size as well as complex colours in the skin.
- The lesion is contrast to the surrounding skin.
- The borders of lesions are not always well defined.
- The influence of small structures, hairs, bubbles, light reflection, and other artifacts.
- The influence of the skin lesions in the surrounding regions.

These factors make the segmentation more complex. To analyze skin lesions, it is necessary to accurately locate and isolate the lesions. The description of the border aspect appears to be an important feature for clinical judgment. Some border descriptors, such as border irregularity and the presence of abrupt border cutters have been considered as predictors of malignancy. Also, the variation in colour signifies the malignancy of the lesion. Hence effective discrimination of the skin lesions was based on the distribution of texture and colour features in this study. A pre-processing step was adopted to remove the influence of skin lesions in the surrounding regions and also the influence of small structures, hairs, bubbles etc.

3.22 MATHEMATICAL MODEL

We model the texture class labels X as a Markov Random Field (MRF) with a four-point nearest neighbor neighborhood system and probability mass function is defined as :

$$P_x(x) = \frac{1}{Z} \exp(-\sum \beta(x_r, x_s) - \sum \gamma(x_r)) \dots \dots (1)$$

Where $\{r,s\}$ belongs to C , Where β and γ_{xr} are MRF model parameters, Z is a normalizing constant, C is the collection of cliques for the MRF, and $t(m; n) = 0$, if $m \neq n$; $t(m;$

$n) = 1$, if m is not equal to n . We will assume that the pixels in the observed image Y can be modeled as conditionally independent Gaussian random variables given the pixel labels X , and that the conditional probability density function of the pixel at location r given X depends only on the value of X at the same pixel location.

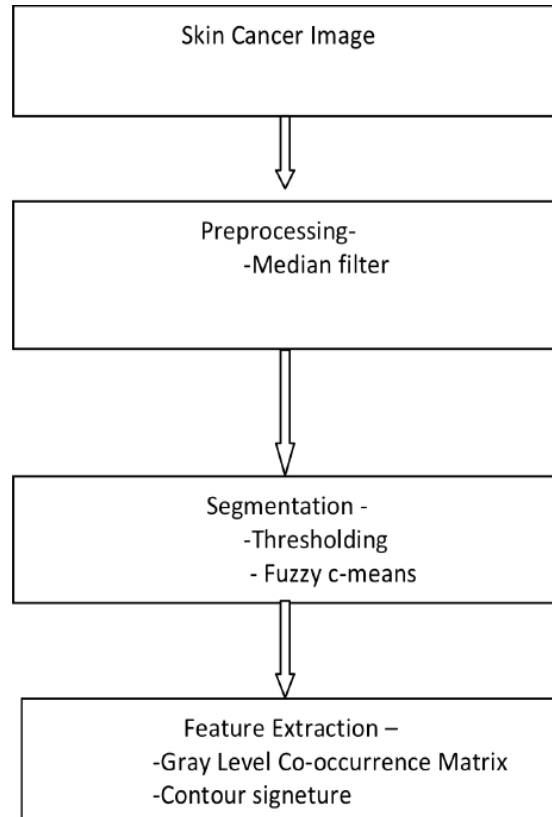


Fig: 5: MATHEMATICAL MODEL

Segmentation is one of the important steps in cancer detection. The aim of segmentation process is to divide the image into homogeneous, self-consistent regions, which should correspond to different objects in the scene. The process is achieved using only properties of image. The properties are edges and texture are useful for segmentation. Image segmentation is the process of partitioning an image into groups of pixels which are homogenous with respect to some criterion. Segmentation is concerned with dividing an image into meaningful regions. Skin cancer image segmentation is based on thresholding. It is an example of pixel based segmentation algorithm. Thresholding techniques produce segments having pixels with similar intensities. Thresholding is a technique for shape analysis, chemistry. Fuzzy C-Means

segmentations is based on partial clustering. Fuzzy C-Means is more flexible. Algorithm for Fuzzy C-Means

1. Initialize the cluster center.
2. Initialize the fuzzy partition membership function.
3. Again compute new cluster center.
4. Repeat step 2 to 3.

In the skin cancer image, cancer is clearly seen by using anisotropic diffusion filter. Thus, we can divide segmentation image into two parts object and background part.

There are some important features that distinguish skin cancer. Feature extraction extracts important features of image data from the segmentation image. It makes the raw data more useful in processing. By feature extraction, the image data is narrow down to a set of features. Feature extraction technique used is Gray Level Co-occurrence Matrix (GLCM). The GLCM is tool for image feature extraction by mapping the gray level co-occurrence probabilities based on spatial relations of pixels in different angular directions. The feature extracted based on GLCM are: Contrast, Correlation, Energy, and Homogeneity. Contrast is the measure of contrast or local intensity variation of pixel. Correlation is a measure of gray level linear dependence between the pixel at specified positions relative to each other. A homogeneous scene will contain only a few gray levels. It provides GLCM with only a few but relatively high values. Energy is returns the sum of squared elements in the GLCM. The features selected are shown in table 1. Shape of image is nothing but distance of all the point on its boundary from some reference point. Its also called contour signature. This reference point is centroid of image. Center of circle is its centroid and distances of all points from center are equal. For square it will be different. In this case we have considered points on the boundary of the image which are separated by angle of 10 degrees. All the angle are measured from center of image. Thus we have calculated 36 distance corresponding to 36 different angles separated by 10 degrees. This angle separation can be reduced in order to increase accuracy. But along with reduction in angle separation, number of reading will increase and it will increase computation time. So there is tread off between ability of system to work in real time and its accuracy.

3.23 Texture Feature extraction

GLCM Features (Gray Level Co-Occurrence Matrix)

It is a statistical method that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (I, J) in the resultant GLCM is simply the sum of the number of times that the pixel with value I occurred in the specified spatial relationship to a pixel with value J in the input image.

The Following GLCM features were extracted in our research work: Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity Energy, Entropy, Homogeneity, Maximum probability , Sum of squares, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation, information measure of correlation, Inverse difference normalized.

Rearrange all above features into the matrix and store it as a database. (Few Image training)

Rest of the images will be tested

3.24 FSVM Classifier

1. Training
2. Testing

Comparison between Trained database and testing input image. The Hidden layer of the SVM classifier will classify the class.

3.25 List of Features

3.25.1 CONTRAST

Contrast is the difference in luminance or color that makes an object (or its representation in an image or display) distinguishable. In visual perception of the real world, contrast is

determined by the difference in the color and brightness of the object and other objects within the same field of view.

3.25.2 AUTOCORRELATION

Autocorrelation measures the correlation between the elements of the matrix. When correlation is high, the image will be more complex than when correlation is low.

3.25.3 CROSS CORRELATION

Cross correlation are basic operations that we will perform to extract information from images. They are in some sense the simplest operations that we can perform on an image, but they are extremely useful. Moreover, because they are simple, they can be analyzed and understood very well, and they are also easy to implement and can be computed very efficiently.

3.25.4 CLUSTER SHADE AND CLUSTER PROMINENCE

Cluster shade and cluster prominence are measures of the skewness of the matrix, in other words the lack of symmetry. When cluster shade and cluster prominence are high, the image is not symmetric. In addition, when cluster prominence is low, there is a peak in the co-occurrence matrix around the mean values. For the image, this means that there is little variation in gray-scales.

3.25.5 DISSIMILARITY

The dissimilarity is a measure of the evenness with which two groups are distributed across the component geographic areas that make up a larger area. The index score can also be interpreted as the of one of the two groups included in the calculation that would have to move to different geographic areas in order to produce a distribution that matches that of the larger area. The index of dissimilarity can also be used as a measure of inequality.

3.25.6 SUM OF SQUARES

In statistical data analysis the total sum of squares is a quantity that appears as part of a standard way of presenting results of such analyses. It is defined as being the sum, over all observations, of the squared differences of each observation from the overall mean.

3.25.7 SUM OF AVERAGE

Sum of average is the sum of a list of numbers divided by the number of numbers in the list. In mathematics and statistics, this would be called the arithmetic mean. However, the word average may also refer to the median, mode, or other central or typical value.

3.25.8 Sum of Variance

The average of the **squared** differences from the Mean of the image. The index score can also be interpreted as the of one of the two groups included in the calculation that would have to move to different geographic areas in order to produce a distribution that matches that of the larger area.

3.25.9 Image Entropy

$E = \text{entropy}(I)$ returns E , a scalar value representing the entropy of grayscale image I . Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as $-\sum(p_i \cdot \log_2(p_i))$

Homogeneity

Image homogeneity is defined as the mean of the luminance of the image. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

Inverse difference normalization

Brightness is the visual perception of reflected light. Increased brightness refers to an image's increased luminance.

Normalized Cross correlation using PCA algorithm

The normalized image has the Principle Components Analysis like Brightness, Contrast and illumination. The sum of average of Brightness, contrast and illumination is called normalized cross correlation using PCA algorithm.

3.26 Statistical Learning Theory

The statistical learning theory provides a framework for studying the problem of gaining knowledge, making predictions, making decisions from a set of data. In simple terms, it enables the choosing of the hyper plane space such a way that it closely represents the underlying function in the target space.

In statistical learning theory the problem of supervised learning is formulated as follows. We are given a set of training data $\{(\mathbf{x}_1, y_1) \dots (\mathbf{x}_l, y_l)\}$ in $\mathbb{R}^n \times \mathbb{R}$ sampled according to unknown probability distribution $P(\mathbf{x}, y)$, and a loss function $V(y, f(\mathbf{x}))$ that measures the error, for a given $\mathbf{x}$, $f(\mathbf{x})$ is "predicted" instead of the actual value y . The problem consists in finding a function f that minimizes the expectation of the error on new data that is, finding a function f that minimizes the expected error: $\int V(y, f(\mathbf{x})) P(\mathbf{x}, y) d\mathbf{x} dy$

In statistical modeling we would choose a model from the hypothesis space, which is closest (with respect to some error measure) to the underlying function in the target space. More on statistical learning theory can be found on introduction to statistical learning theory.

3.27 Convolutional Neural Network classification

Learning and Generalization

Early machine learning algorithms aimed to learn representations of simple functions. Hence, the goal of learning was to output a hypothesis that performed the correct classification of the training data and early learning algorithms were designed to find such an accurate fit to the data. The ability of a hypothesis to correctly classify data not in the training set is known as its generalization. SVM performs better in term of not over generalization when the neural networks might end up over generalizing easily. Another thing to observe is to find where to

make the best trade-off in trading complexity with the number of epochs; the illustration brings to light more information about this. The below illustration is made from the class notes.

Introduction to CNN

Firstly working with neural networks for supervised and unsupervised learning showed good results while used for such learning applications. MLP's uses feed forward and recurrent networks. Multilayer perceptron (MLP) properties include universal approximation of continuous nonlinear functions and include learning with input-output patterns and also involve advanced network architectures with multiple inputs and outputs.

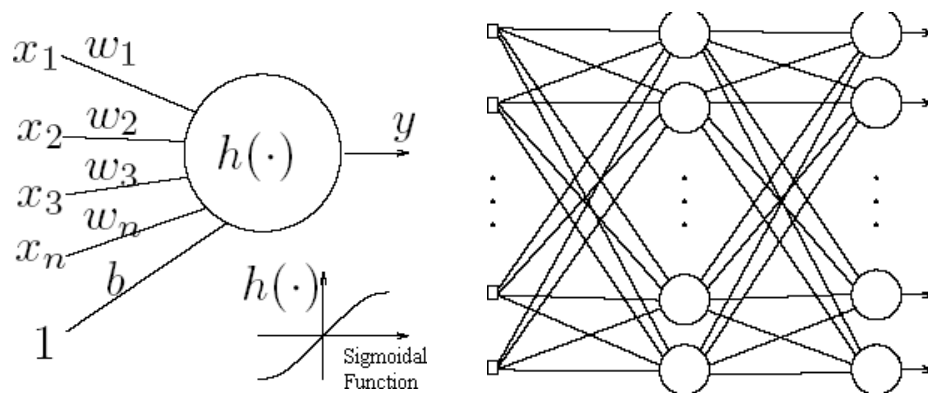


Figure 6: Simple Neural Network b) Multilayer Perceptron. These are simple visualizations just to have a overview as how neural network looks like.

There can be some issues noticed. Some of them are having many local minima and also finding how many neurons might be needed for a task is another issue which determines whether optimality of that NN is reached. Another thing to note is that even if the neural network solutions used tends to converge, this may not result in a unique solution. Now let us look at another example where we plot the data and try to classify it and we see that there are many hyper planes which can classify it.

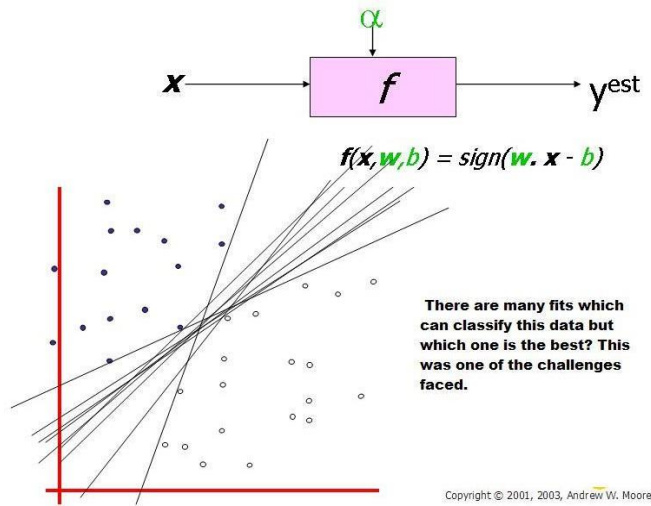


Figure 7: Here we see that there are many hyper planes which can be fit in to classify the data but which one is the best is the right or correct solution. The need for CNN arises. Note the legend is not described as they are sample plotting to make understand the concepts involved.

From above illustration, there are many linear classifiers (hyper planes) that separate the data. However only one of these achieves maximum separation. The reason we need it is because if we use a hyper plane to classify, it might end up closer to one set of datasets compared to others and we do not want this to happen and thus we see that the concept of maximum margin classifier or hyper plane as an apparent solution. The next illustration gives the maximum margin classifier example which provides a solution to the above mentioned problem.

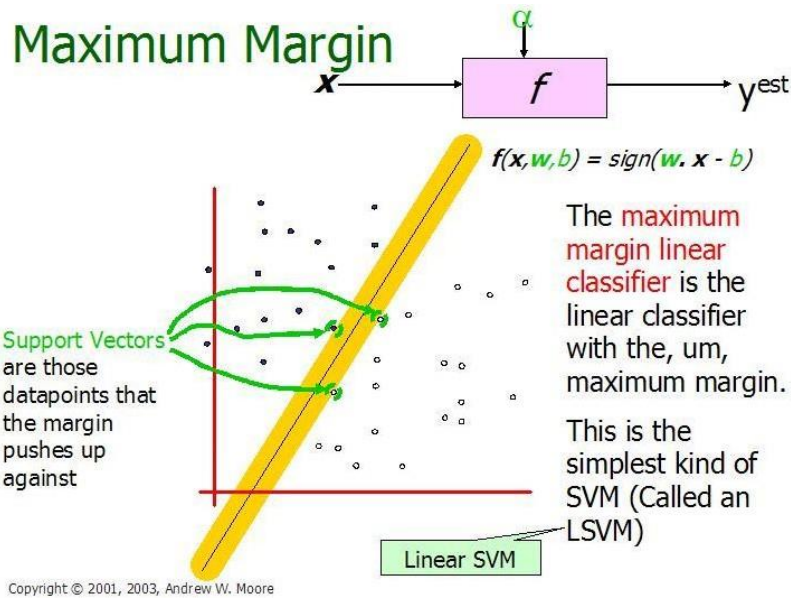


Figure 8: Illustration of Linear CNN. Note the legend is not described as they are sample plotting to make understand the concepts involved.

Expression for Maximum margin is given as (for more information visit):

$$\text{margin} = \arg \min_{\mathbf{x} \in D} d(\mathbf{x}) = \arg \min_{\mathbf{x} \in D} \frac{|\mathbf{x} \cdot \mathbf{w} + b|}{\sqrt{\sum_{i=1}^d w_i^2}}$$

The above illustration is the maximum linear classifier with the maximum range. In this context it is an example of a simple linear CNN classifier. Another interesting question is why maximum margin? There are some good explanations which include better empirical performance. Another reason is that even if we've made a small error in the location of the boundary this gives us least chance of causing a misclassification. The other advantage would be avoiding local minima and better classification. Now we try to express the CNN mathematically and for this tutorial we try to present a linear CNN. The goals of CNN are separating the data with hyper plane and extend this to non-linear boundaries using kernel trick. For calculating the CNN we see that the goal is to correctly classify all the data. For mathematical calculations we have,

[a] If $Y_i = +1$; $w x_i + b \geq 1$

[b] If $Y_i = -1$; $w x_i + b \leq -1$

$$[c] \text{ For all } i; \quad y_i (w_i + b) \geq 1$$

In this equation x is a vector point and w is weight and is also a vector. So to separate the data [a] should always be greater than zero. Among all possible hyper planes, CNN selects the one where the distance of hyper plane is as large as possible. If the training data is good and every test vector is located in radius r from training vector. Now if the chosen hyper plane is located at the farthest possible from the data. This desired hyper plane which maximizes the margin also bisects the lines between closest points on convex hull of the two datasets.

3.28 CNN for Classification

CNN is a useful technique for data classification. Even though it's considered that Neural Networks are easier to use than this, however, sometimes unsatisfactory results are obtained. A classification task usually involves with training and testing data which consist of some data instances. Each instance in the training set contains one target values and several attributes. The goal of CNN is to produce a model which predicts target value of data instances in the testing set which are given only the attributes.

Classification in CNN is an example of Supervised Learning. Known labels help indicate whether the system is performing in a right way or not. This information points to a desired response, validating the accuracy of the system, or be used to help the system learn to act correctly. A step in CNN classification involves identification as which are intimately connected to the known classes. This is called feature selection or feature extraction. Feature selection and CNN classification together have a use even when prediction of unknown samples is not necessary. They can be used to identify key sets which are involved in whatever processes distinguish the classes.

CNNs can also be applied to regression problems by the introduction of an alternative loss function. The loss function must be modified to include a distance measure. The regression can be linear and nonlinear. Linear models mainly consist of the following loss functions, e-intensive loss functions, quadratic and Huber loss function. Similarly to classification problems, a non-linear model is usually required to adequately model data. In the same manner as the non-linear SVC approach, a non-linear mapping can be used to map the data into a high dimensional feature space where linear regression is performed.

CHAPTER 4

4.1 RESULTS AND DISCUSSION

Input Image



Figure 1: Input Digital Skin Image

Figure 1 show the input digital skin image of HiFi digital camera imaging process.

AnisotropicDiffusion Restored Image



Figure 2: Anisotropic Diffusion Filter

Figure 2 show in image processing and computer vision, **anisotropic diffusion**, also called Perona–Malik **diffusion**, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image.

Difference Between Input Image and Output Image

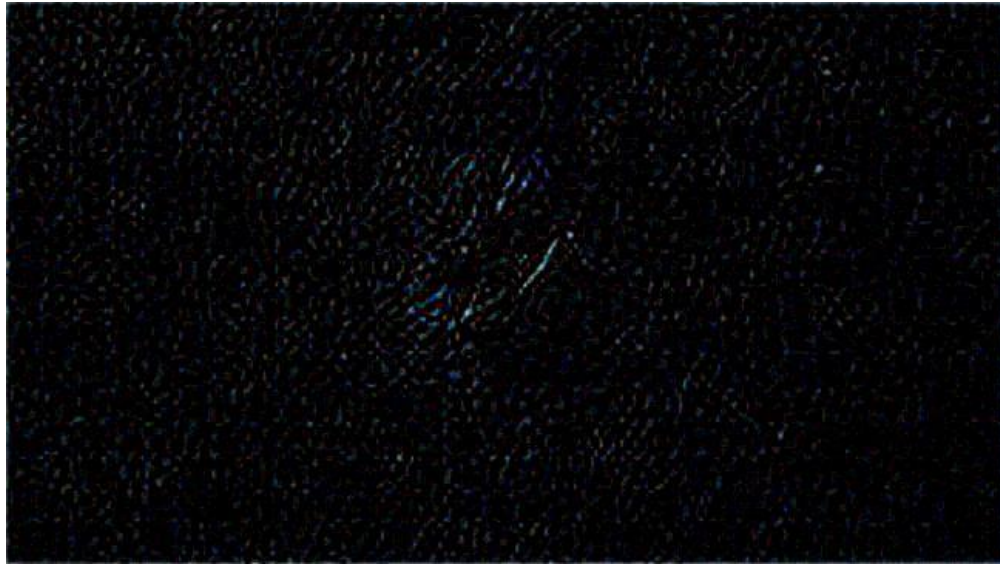


Figure 3: The eliminated noise on the input raw digital image

Image Enhancement



Figure 4: Low quality digital image is converted into the high quality digital image

Figure 4 shows Image enhancement is the process of adjusting digital images so that the results are more suitable for display or further image analysis. For example, you can remove noise, sharpen, or brighten an image, making it easier to identify key features.

Figure 5: Gray converted Image which have 0 to 255 gray scale values throughout the matrix

Figure 5 shows Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured.

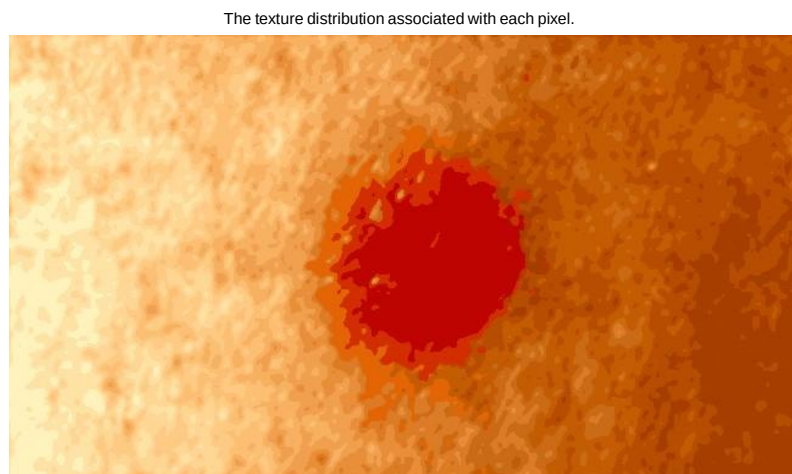


Figure 6: the texture distribution associated with each pixel

Figure 6 shows the texture format of the image. The K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The points are clustered around centroids.

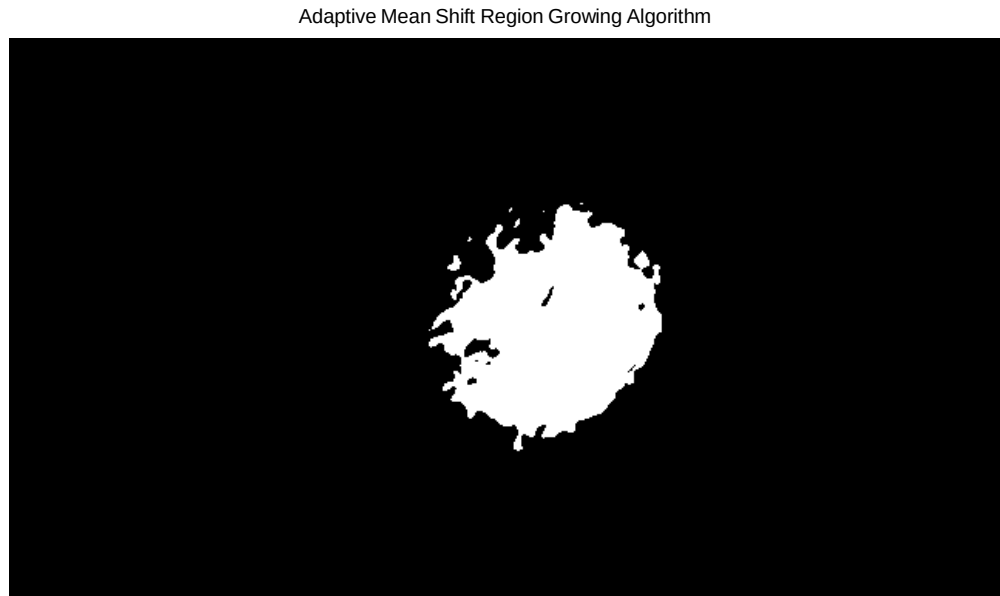


Figure 7: Adaptive Fast Fuzzy C Means Clustering Segmentation

Figure 7 shows the adaptive mean region growing segmented image of skin cancer pixels. Adaptive Mean Region growing is accurate region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points.

CONCLUSION

Skin cancer in both melanoma and non-melanoma types is common and leads to many yearly deaths worldwide. Early diagnosis has been shown to drastically reduce therapy time, cost, and suffering from the prolonged traditional treatment methods (e.g., chemotherapy). However, accurate screening/diagnosis requires specialist knowledge of the different types of cancers and how they appear in the form of skin lesions. Some people may ignore such lesions due to ignorance, indifference, cost, or doctor appointment scheduling delays. Recently, the field of deep learning and artificial intelligence has opened the door for the development of reliable image-based medical systems for screening and diagnosis. In this project, we have used a well-known dermoscopy dataset of seven common types of cancerous skin lesions, utilized recent advances in the design of deep convolutional neural networks, and applied deep transfer learning to the application of screening/diagnosing skin lesion images. Such an approach has the capability to achieve high accuracies that reduce the burden on specialists.

CONSTRAINT

In response to the dramatic rise in melanoma incidence, numerous health care specialists have encouraged primary care providers to increase skin cancer detection efforts. Although primary care providers currently find more melanomas than do dermatologists, many detection opportunities are missed. In addition, primary care providers occasionally incorrectly reassure patients about specific lesions. Nevertheless, there is little evidence that efforts to detect skin cancer are growing. This paper discusses barriers to skin cancer detection and potential ways to increase screening. Skin cancer is the most common cancer in the United States and worldwide. Although the majority of the works in the literature are focused on melanoma detection, the most common malign skin lesion is the skin cancer. Over 95% of NMSC cases are Basal Cell Carcinoma (BCC) and cutaneous squamous cell carcinoma (SCC). Specifically, BCC has an incidence higher than 70% among all skin cancer, it has the best validated clinical criteria for its diagnosis, and it presents the higher variability in the presence of these dermoscopic criteria. The detection of skin disease can be performed by visual inspection by a skilled dermatologist, but there are many benign lesions that can be confused with skin disease, leading to unnecessary biopsies, in a proportion of five biopsies versus one actual cancer case. The increase in the incidence of BCC is provoking an overload for dermatologists. In the Andalusian Health System, dermatology is being implanted. Nowadays, 315 demands of tele-dermatology consultation per month are received and 210 receive diagnostic criteria of BCC.

STANDARDIZATION

Techstreet offers simultaneous access to a custom set of standards in electronic format. Includes automatic updates. Includes ISO standards related to medical devices and health services.

- ASTM Compass (formerly Standards and Engineering Digital Library (SEDL))
- ASTM includes testing, materials, processing of medical devices as well as many other areas.

IEEE Xplore

- IEEE Standards related to biotechnology include electronics and health informatics.
- Materials for Medical Devices
- A comprehensive set of mechanical, physical, biological response, and drug compatibility properties for the materials and coatings used in cardiovascular and orthopaedic medical devices.

FDA - Medical Devices Standards Database

Recognized Consensus Standards for medical devices by FDA. The standards have been developed by the Center of Devices and Radiological Health (CDRH)

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