DIAGNOSIS OF MELANOMA WITH REGION AND CONTOUR BASED FEATURE EXTRACTION AND KNN CLASSIFICATION

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Abstract – Melanoma is becoming more common in different nations; therefore early detection is a viable technique for lowering melanoma mortality rates. Since the diagnosis of skin cancer is prone to human mistake and entails some expenditure and illness, studies are attempting for the automation of this evaluation for determining whether it is harmless or harmful, and for estimating it with an error range which is less than achievements of human. As a result, determining more effective detection methods to lower the error rate in the diagnosis is a critical concern among researchers. Therefore an efficacious approach based on image processing concepts is introduced for the diagnosis of melanoma. A Gaussian smoothing filter is utilized that has specific kernel size hence providing specific energy as well as quality parameters with the reduction of required energy. The edge based and region based information of the images are combined into RGB approach for effective segmentation. The desired texture features which are statistical are extracted by region and contour based approaches indicating the capture of image visual content for retrieval and indexing. The classification and regression of images are performed by KNN classifier in the absence of explicit training phase generating an improved accuracy of 95.9%.

Keywords: Melanoma, Gaussian smoothing filter, RGB segmentation, Region and contour based approach, KNN.

1 INTRODUCTION

Melanoma is particularly a lethal kind of skin cancer, that accounts for 75 percent of skin cancer mortality although accounting for only 4% of all skin malignancies. Melanoma is cured if detected and treated early on; but, if detected later, melanoma spreads in depth into the skin as well as other body regions. Its spreading to rest of body sections, which is difficult to cure, is dangerous. Melanoma is caused by the existence of melanocytes in body portions and is caused by prolonged exposure to UV light on the skin [1-3]. Melanoma is a kind of cancer that begins in pigment cells for almost all cases, resulting in a dark lesion. The lesion might be pink, white, or tan in some situations. Apart from colour, there are various other characteristics of melanomas that distinguish them from benign lesions, such as texture and structure [4-5].

The diagnosis of melanoma is a crucial task and involves error margins and inaccuracy. Hence, improved detection approach is necessary for the diagnosis which demands the utilization of image processing concepts. It generally includes preprocessing, segmentation, feature extraction and classification [6, 7]. Initially, for preprocessing linear filters are utilized which ignore noise as well as picture attributes which are dispersed across the image, resulting in softening of contrast as well as the image's edge region. Speckle noise is successfully reduced by nonlinear filters including an adaptive mean filter [8, 9] as well as a median [10-12] filter. These filters, on the other hand, have the drawback of losing information due to blurring in crucial as well as edge parts of the image. As a result, these filters are ineffective at removing noise. Numerous filters, like the anisotropic diffusion (AD) filter [13-15], is indeed suggested to tackle this problem. For the preservation of boundaries as well as effective elimination of noise, AD filter searches in local directions. The reduction of noise performance of AD filter, on the other hand, varies based on many variables that are modified at a particular resolution. The AD filter's noise reduction performance, on the other hand, is dependent on the numerous variable parameters that are changed at a single resolution. The weights of such filters are determined not only by considering the spatial features of surrounding pixels, but also with the consideration of the shading values of neighbouring pixels, respecting the borders. Nevertheless, relying on the threshold of the parameter for distinguishing noise as well as boundary, these filters have an impact on noise removal performance [16]. Hence a Gaussian smoothing filter is utilized in this approach in effective eradication of noise speckles from input image.

Preprocessing is succeeded with segmentation approach in which the image is subdivided into objects or parts. Many studies have been done on segmentation, yet it is challenging to separate the required regions [17]. The segmentation of images manually demand various restrictions like increased time of processing as well as substantial operator dependency. Hence introducing computer dependent approaches for the segmentation of images is important for achieving reliable as well as automated systems [18]. If the nearest neighbour meets the thresholding criterion, regions are grown to segment the desired areas in region-based approaches [19]. Thresholding is a common monochrome technique for image segmentation. [20-22] used thresholding segmentation to isolate the tumor region from the background before using edge detection to find the beginning border. When the skin as well as lesion histogram modes overlap, segmentation becomes difficult and cannot be accomplished utilizing thresholding. Therefore robust graph-based (RGB) approach is deployed for image segmentation.

Following image segmentation, the extraction of textural features from the images is to be carried out. A simple as well as most effective approach for the reduction of dimensionality in image processing is feature extraction [23]. The subsequent information from the image given as input for reduction approach is extracted using the extracted or selected set of features [24]. For various imaging modalities and cancer types, many feature extraction methods have been examined [25-26]. However, past research has primarily focused on building good feature descriptors that are used in conjunction with machine learning approaches to understand context from medical imaging. These feature extraction-based approaches have a number of flaws [27]. Due to these limitations, region as well as contour based approaches are adopted for effective feature extraction in images.

Finally, classification of images is to be performed with improved accuracy. Since the technique of scanning as well as uploading images for diagnosis to a computer has become simpler in recent years, several research are being done to find and classify tumours using a variety of automated approaches [28]. In this approach, K-nearest neighbour classifier (KNN) is deployed for the enhanced classisfication of images with inceased accuracy. Henceforth, the contributions of this approach are given as follows: A Gaussian smoothing filter for image preprocessing and edge based approach for image segmentation is performed. Efficacious feature extraction is carried out by region as well as contour based approaches and classification is done by KNN approach.

The succeeding part of this work comprises of: Section 2 with related works, section 3 includes proposed topology, section 4 with attained results and section 5 includes conclusion.

2 RELATED WORKS

Achim et al [29] described an experiment regarding the combination of artificial intelligence as well as human for classifying the images related to skin cancer. Initially, the images were classified into five categories and later they were identified whether they are benign or malignant. This combination indicated superior results but are regarded as non-significant.

Nilanjan et al [30] introduced an optimization approach for the skin cancer diagnosis which involved pre-processing as well as post-processing of images. The results were obtained utilizing datasets of dermoscopy images. Similarity metrics were adopted for the evaluation of clinical significance of the tumor images.

Roberta et al [31] presented a computational approach which described a novel feature extraction of skin lesions. It relies on the analysis of texture, border, colour and asymmetry of images. The classification as well as segmentation of images were performed depending on diffusion filter which is anisotrophic in nature.

Balazs et al [32] proposed a novel methodology which involves the classifier outputs' fusion. The ensemble of various neural networks was created and hence the startegies applied for fusion overcame each network corresponding to accuracy. Subsequently, this improved the accuracy of classification in the detection of melanoma in images.

3 PROPOSED TOPOLOGY

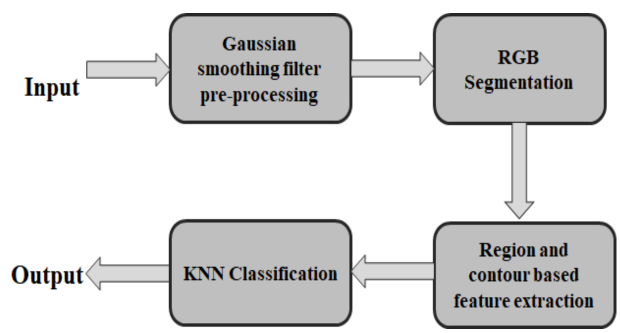


Figure 1 Proposed block diagram

The flow diagram of the introduced approach is given in figure 1. The input image of skin with cancer cells is fed to the Gaussian smoothing filter for removing noise and this preprocessed image is segmented by means of RGB segmentation. Subsequently, region and contour based approach is exploited for the extraction of image features offering enhanced compatibility. Finally KNN classifier is adopted for efficient prediction and classification of images.

3.1 Gaussian Smoothing Filter Preprocessing

A Gaussian filter is regarded as an averaging filter utilized for various concepts of image processing like blurring, segmenting and detecting images. The efficiency of image processing concepts depend on the performance of the Gaussian filter. The Gaussian smoothing filter is generally utilized for the smoothening of images. Considering zero mean (μ) as well as constant standard deviation (σ), the gaussian function is given by,

$$G(a,b) = \exp(-(a^2+b^2)/2\sigma^2) \quad (1)$$

Here, a, b: variables

The Gaussian distribution performs the convolution of images with the distribution function regarded as a point-spread function. For the approximation of Gaussian function in discrete time, a large convolution kernel is required and hence the values greater than $\pm 3\sigma$ with the distribution equal to zero are neglected.

The kernel coefficient values vary inversely with the distance parameter. The blurring quantity relies on the peak width and when the sigma value is greater, the peak is wider. For maintaining the Gaussian property of the filter the kernel size is to be increased with the increase in sigma. The coefficients of the kernel rely on the sigma value and the kernel is symmetric with respect to the centre in the absence of directional bias. For the efficient implementation of Gaussian function, approximation utilizing the coefficients generally termed as kernel is to be performed. The σ value is taken as greater value for improved smoothing and the size of the kernel is to be large for the accurate representation. For the smoothened value of the pixel, the extraction of a 5×5 sub-matrix image is performed with the pixel and the multiplication of the kernel with the sub-matrix of the image is carried out. Moreover, the kernel coefficients'total is to be considered as one which indicates the normalization of coefficients' sum for maintaining the level of intensity of the image.

3.2 RGB Segmentation

The input image is considered as a graph and the neighbouring pixels of same intensity are merged as a minimal spanning tree (MST) regarded as a subgraph. The image is subdivided into various subregions and the merging of pixels determines the segmentation outputs. Consider a graph, $G=(X,Y)$ with predicate $P(Q_1,Q_2)$ that compares the differences of the intersubgraph with differences of the within-subgraphs.

$$P(Q_1,Q_2) = \begin{cases} false, \ when \ diff(Q_1,Q_2) > mInt(Q_1,Q_2) \\ true, \ other \end{cases} \quad (2)$$

$$\text{Diff } (Q_1,Q_2) = |\mu(Q_1) - \mu(Q_2)| \quad (3)$$

$$mInt(Q_1,Q_2) = \min(\sigma(Q_1) + \tau(Q_1), \sigma(Q_2) + \tau(Q_2)) \quad (4)$$

$$\tau(Q) = \frac{k}{|Q|}\left(1+\frac{1}{\alpha\beta}\right) \quad (5)$$

Where, $\beta = \frac{\mu(Q)}{\sigma(Q)}$ (6)

$diff(Q_1,Q_2)$: difference between two subgraphs Q_1 and $Q_2 \in$ V, $mInt(Q_1,Q_2)$: minimal internal difference of Q_1 and Q_2

$\mu(Q)$: average intensity of Q

$\sigma(Q)$: standard deviation of Q

$\tau(Q)$: threshold function of Q

α, k : positive parameters

With the increase in k, τ increases and the merging of regions become more easy. The steps carried out for the image segmentation are given by,

1) Consider a graph $G=(X,Y)$ for the input image. Every pixel represents a vertex and every edge links neighbouring vertices.
2) Arrange the edges of Y in non descending order of the weight of the edge and consider q=1.
3) Select the dth edge of Y and if it is an invalid one connecting two subgraphs, these subgraphs are merged to form a larger one thus becoming valid. Consider $d=d+1$ and repeat this step till the traversing of all edges.

3.3 Region and Contour Based Feature Extraction

Following segmentation of images, the desired features are extracted for detecting and grading potential cancers. Extracting features is a crucial step in the investigation of cancer images. The extraction of features is performed at cell level as well as tissue level of images for improved prediction.In order to extract the information of shapes in an enhanced manner, region and contour based method is utilized for the extraction of desired features. The feature of the cellular level concentrates on the quantification of the cell properties neglecting the spatial dependency of cells. The features extracted by the utilized approach are textural features, morphological features, wavelet features and histogram features. Certain features related to morphology and shape are given below.

i) Area of the Nucleus:

The area of the nucleus is denoted by the region of the nucleus consisting the total count of pixels and is given by,

$$A = \sum_{i=1}^{n}\sum_{j=1}^{m} I(i,j) \quad (7)$$

Here, : area of the nucleus

I : segmented image

ii) Solidity:

It is defined as the ratio of the nucleus area to the convex area.

$$Solidity = \frac{Area\ of\ the\ nucleus}{Convex\ area} \quad (8)$$

iii) Eccentricity:

It denotes the ratio of major axis length to the minor axis length.

$$Eccentricity = \frac{major\ axis\ length}{minor\ axis\ length} \quad (9)$$

iv) Compactness:

It denotes the ratio of area to the square of the perimeter.

$$Compatness = \frac{area}{perimeter^2} \quad (10)$$

v) Longest Diameter (LD) of the Nucleus:

It represents the diameter of the largest circle that circumscribe the region of the nucleus.

$$LD = \sqrt{(a_1 - a_2)^2 + (b_1 - b_2)^2} \quad (11)$$

Here, a_1, a_2, b_1, b_2: end points on major axis

vi) Shortest Diameter (SD) of the Nucleus:

It represents the diameter of the smallest circle that circumscribe the region of the nucleus.

$$LD = \sqrt{(a_2 - a_1)^2 + (b_2 - b_1)^2} \quad (12)$$

3.4 KNN Classifier

KNN is utilized for classification and regression and is considered as a nonparametric classifier. It does not require any training phase and the centroid is regarded as the centre of specific cluster as shown in figure 2.

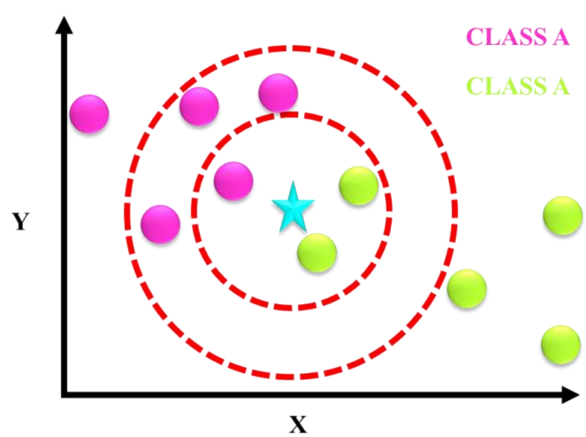


Figure 2 Basic KNN approach

In this approach, the data is partitioned into training set as well as test set. Each test set row of the k neighbor which is nearest depending on the Euclidean distance is observed based on the following equation.

$$ED = \|y_i - x_i\| = \left|\sum_{j=1}^{n} \left|\frac{|y_{ij} - x_{ij}|^2}{n}\right|\right| \quad (13)$$

Here, x_i : training data

y_i : test data

n : total number of features

The classifier determines k nearest neighbours of the training set which are closer to unknown neighbours. For the classification of unlabeled neighbours, the distance between the labeled neighbour and the unlabeled neighbour is computed. The classification is performed utilizing the nearness of the unlabeled to labeled neighbor depending on the function of distance.

3.4.1 KNN Algorithm

Step 1: Obtain the training data set and the unlabeled test data.

Step 2: Estimate the distance between each training data and unlabeled test data.

Step 3: Select the group of nearest neighbour to the unlabeled one.

Step 4: Generate the test data with the nearest neighbour's majority class.

4 RESULTS AND DISCUSSION

The dataset utilized for the melanoma diagnosis is PH2 dataset. It includes the segmentation, diagnosis as well as identification of images related to dermoscopy and the obtained images are given below.

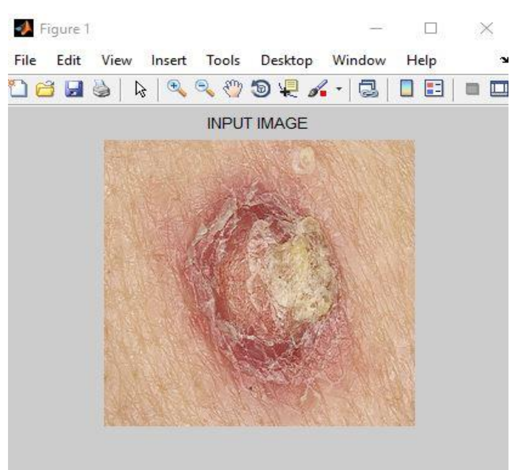


Figure 3 Input image

Figure 3 indicates the image of skin affected with melanoma given as input.

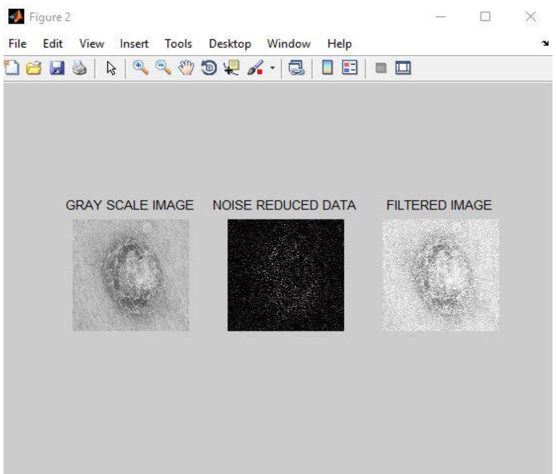


Figure 4 Filtered image

Figure 4 indicates the image filtered with the utilized Gaussian smoothing filter and figure 5 indicates the enhanced output image. The output clearly denotes that the image is free from noise.

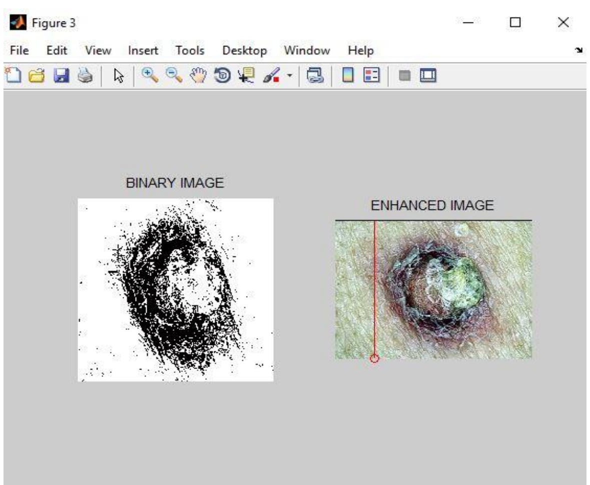


Figure 5 Enhanced image

Figure 6 represents the clustered image and figure 7 indicates the segmented image obtained as a result of RGB approach.

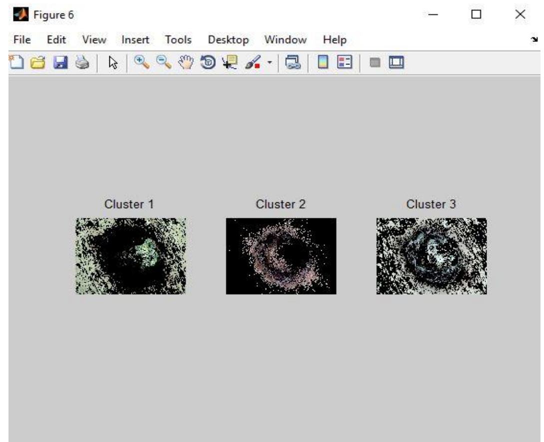


Figure 6 Clustered image

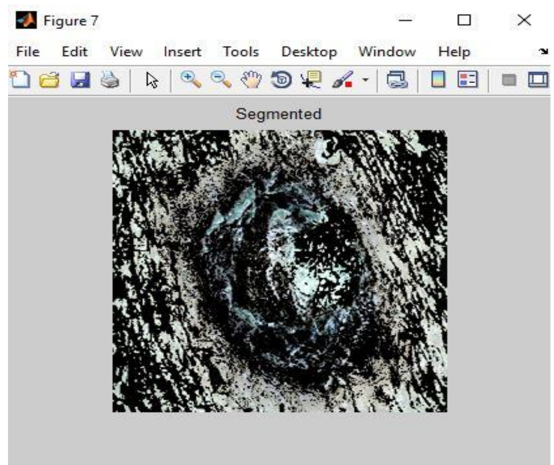
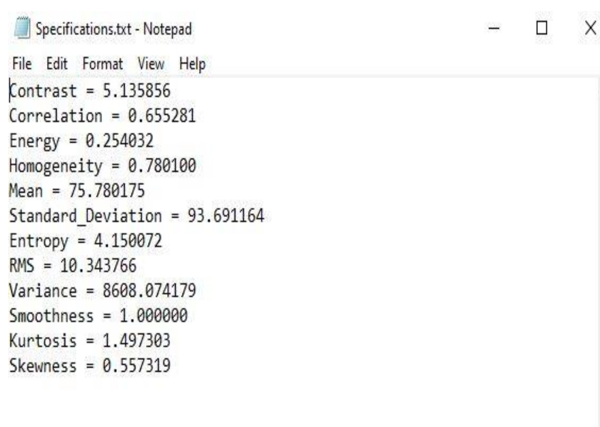


Figure 7 Segmented image


Specifications.txt - Notepad

Contrast = 5.135856
Correlation = 0.655281
Energy = 0.254032
Homogeneity = 0.780100
Mean = 75.780175
Standard_Deviation = 93.691164
Entropy = 4.150072
RMS = 10.343766
Variance = 8608.074179
Smoothness = 1.000000
Kurtosis = 1.497303
Skewness = 0.557319

Figure 8 Extracted features

Figure 8 represents the features extracted utilizing the region and contour based approach for the testing as well as training procedure.

4.1 Performance Indicators

The performance analysis for the below mentioned metrics are done in this approach.

i) Accuracy

Accuracy represents the percentage of appropriately classified instances and is expressed as,

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

ii) Precision

Precision is regarded as the correctness degree for the determination of outcomes which are positive and is expressed as,

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

iii) Recall

It denotes the effectiveness measure of the system for the prediction of positive as well as cost determination and is expressed as,

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

iv) F1 Score

It denotes the weighted average of recall as well as precision and is expressed as,

$$\text{F1}= \frac{2*(Precision*recall)}{(Precision+recall)}$$

Where TP→ True Positive
TN→ True Negative
FP→ False Positive
FN→False Negative

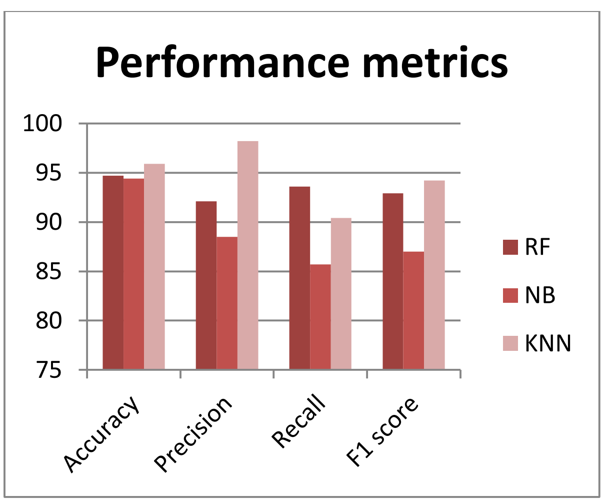


Figure 9 Comparison graph

Figure 9 indicates the comparison of KNN with Naïve Bayes classifier and Random forest classifier in which the utilized KNN revealed improved results with an accuracy of 95.9%.

5 CONCLUSION

Melanoma is a major serious and belligerent skin cancer type, thus it's critical to detect it early. An automated melanoma detection system is required to minimize the cost as well as enhance the accuracy of the detection procedure. Hence, an improved method based on image processing concepts is discussed in this article for detecting melanoma. From the obtained results it is finalized that the proposed approach can be effectively utilized for accurate skin cancer diagnosis. All of the processes for enhancing skin cancer images, as well as the filter for removing noise and smoothening the images are described.

References

[1] Jain, Shivangi, and Nitin Pise, “Computer aided melanoma skin cancer detection using image processing”, Procedia Computer Science, Vol. 48, pp. 735-740, 2015.

[2] Ansari, Uzma Bano, and Tanuja Sarode, “Skin cancer detection using image processing”, Int Res J Eng Technol, Vol. 4, No. 4, pp. 2875-2881, 2017.

[3] Dascalu, Avi, and E. O. David, “Skin cancer detection by deep learning and sound analysis algorithms: A prospective clinical study of an elementary dermoscope”, EBioMedicine, Vol. 43, pp. 107-113, 2019.

[4] Garg, Nishtha, Vishakha Sharma, and Prabhjot Kaur, “Melanoma skin cancer detection using image processing”, Sensors and Image Processing, Springer Singapore, 2018.

[5] Yas, Qahtan M., A. A. Zaidan, B. B. Zaidan, M. Hashim, and Chen Kim Lim, “A systematic review on smartphone skin cancer apps: coherent taxonomy, motivations, open challenges and recommendations, and new research direction”, Journal of Circuits, Systems and Computers, Vol. 27, No. 05, 2018.

[6] Hoshyar, Azadeh Noori, Adel Al-Jumaily, and Afsaneh Noori Hoshyar, “The beneficial techniques in preprocessing step of skin cancer detection system comparing”, Procedia Computer Science, Vol. 42, pp. 25-31, 2014.

[7] Jaiswar, Sanjay, Mehran Kadri, and Vaishali Gatty, “Skin cancer detection using digital image processing”, International Journal of Scientific Engineering and Research, Vol. 3, No. 6, pp. 138-140, 2015.

[8] Thanh, Dang Ngoc Hoang, and Serdar Engínoğlu, “An iterative mean filter for image denoising”, IEEE Access, Vol. 7, pp. 167847-167859, 2019.

[9] Fareed, Samsad Beagum Sheik, and Sheeja Shaik Khader, “Fast adaptive and selective mean filter for the removal of high-density salt and pepper noise”, IET Image Processing, Vol. 12, No.8 , pp. 1378-1387, 2018.

[10] Erkan, Uğur, Levent Gökrem, and Serdar Enginoğlu, “ Different applied median filter in salt and pepper noise”, Computers & Electrical Engineering, Vol. 70, pp. 789-798, 2018.

[11] Verma, Kesari, Bikesh Kumar Singh, and A. S. Thoke, “An enhancement in adaptive median filter for edge preservation”,Procedia Computer Science, Vol.48, pp.29-36, 2015.

[12] Kumar, N. Rajesh, and J. Uday Kumar, “A spatial mean and median filter for noise removal in digital images”, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 4, No. 1, pp. 246-253, 2015.

[13] Nair, Resmi R., Ebenezer David, and Sivakumar Rajagopal, “A robust anisotropic diffusion filter with low arithmetic complexity for images”, EURASIP Journal on Image and Video Processing, Vol. 1, pp. 1-14, 2019.

[14] Malarvel, Muthukumaran, Gopalakrishnan Sethumadhavan, Purna Chandra Rao Bhagi, Soumitra Kar, Thangavel Saravanan, and Arunmuthu Krishnan, “Anisotropic diffusion based denoising on X-radiography images to detect weld defects”, Digital Signal Processing, Vol. 68, pp.112-126, 2017.

[15] Xu, Jiangtao, Yuanyuan Jia, Zaifeng Shi, and Ke Pang, “An improved anisotropic diffusion filter with semi-adaptive threshold for edge preservation”, Signal Processing, Vol. 119, pp. 80-91, 2016.

[16] Choi, Hyunho, and Jechang Jeong, “Despeckling images using a preprocessing filter and discrete wavelet transform-based noise reduction techniques”,IEEE Sensors Journal, Vol. 18, No. 8, pp.3131-3139, 2018.

[17] Prasad, B. S., “Detection of masses in mammogram based on non-linear filtering techniques”, Journal of Medical and Bioengineering, Vol. 4, No. 6, pp. 430-435, 2015.

[18] Daoud, Mohammad I., Ayman A. Atallah, Falah Awwad, Mahasen Al-Najjar, and Rami Alazrai, “Automatic superpixel-based segmentation method for breast ultrasound images”,Expert Systems with Applications, Vol.121, pp. 78-96, 2019.

[19] Makandar, Aziz, and Bhagirathi Halalli, “Threshold based segmentation technique for mass detection in mammography”, J. Comput., Vol.11, No. 6, pp. 472-478, 2016.

[20] Ilhan, Umit, and Ahmet Ilhan, “Brain tumor segmentation based on a new threshold approach”, Procedia computer science, Vol. 120, pp. 580-587, 2017.

[21] Varga-Szemes, Akos, Giuseppe Muscogiuri, U. Joseph Schoepf, Julian L. Wichmann, Pal Suranyi, Carlo N. De Cecco, Paola M. Cannaò et al, “Clinical feasibility of a myocardial signal intensity threshold-based semi-automated cardiac magnetic resonance segmentation method”,European radiology, Vol. 26, No. 5, pp. 1503-1511, 2016.

[22] Riaz, Farhan, Sidra Naeem, Raheel Nawaz, and Miguel Coimbra, “Active contours based segmentation and lesion periphery analysis for characterization of skin lesions in dermoscopy images”, IEEE journal of biomedical and health informatics, Vol.23, No.2, pp. 489-500, 2018.

[23] X. Sui, W. Jiang, H. Chen, F. Yang, J. Wang, Q. Wang, “Validation of the stage groupings in the eighth edition of the tnm classification for lung cancer”, J.Thoracic Oncol. Vol.12 , No.11, pp. 1679–1686, 2017.

[24] Lakshmanaprabu, S. K., Sachi Nandan Mohanty, K. Shankar, N. Arunkumar, and Gustavo Ramirez, “Optimal deep learning model for classification of lung cancer on CT images”, Future Generation Computer Systems, Vol.92, pp. 374-382, 2019.

[25] Han, H. Wang, G. Zhang, H. Han, B. Song, L. Li, W. Moore, H. Lu, H. Zhao, Z. Liang, “Texture feature analysis for computer-aided diagnosis on pulmonary nodules”, Journal of digital imaging, Vol.28, pp.99-115, 2015.

[26] N.J. Tustison, K. Shrinidhi, M. Wintermark, C.R. Durst, B.M. Kandel, J.C. Gee, M.C. Grossman, B.B. Avants, “Optimal symmetric multimodal templates and concatenated random forests for supervised brain tumor segmentation (simplified) with ANTsR”, Neuroinformatics, Vol.13, pp. 209-225, 2015.

[27] Hu, Zilong, Jinshan Tang, Ziming Wang, Kai Zhang, Ling Zhang, and Qingling Sun, “Deep learning for image-based cancer detection and diagnosis− A survey”,Pattern Recognition, Vol. 83, pp. 134-149, 2018.

[28] Afnan M. Alhassan;Wan Mohd Nazmee Wan Zainon, “BAT Algorithm With fuzzy C-Ordered Means (BAFCOM) Clustering Segmentation and Enhanced Capsule Networks (ECN) for Brain Cancer MRI Images Classification”, IEEE Access, Vol. 8, pp. 201741 – 201751, 2020.

[29] Hekler, Achim, Jochen S. Utikal, Alexander H. Enk, Axel Hauschild, Michael Weichenthal, Roman C. Maron, Carola Berking et al, “Superior skin cancer classification by the combination of human and artificial intelligence”,European Journal of Cancer, Vol. 120, pp.114-121, 2019.

[30] Dey, Nilanjan, Venkatesan Rajinikanth, Amira S. Ashour, and João Manuel RS Tavares, "Social group optimization supported segmentation and evaluation of skin melanoma images", Symmetry, Vol.10, No. 2, 2018.

[31] Oliveira, Roberta B., Norian Marranghello, Aledir S. Pereira, and João Manuel RS Tavares, "A computational approach for detecting pigmented skin lesions in macroscopic images", Expert Systems with Applications, Vol. 61, pp. 53-63, 2016.

[32] Harangi, Balazs, "Skin lesion classification with ensembles of deep convolutional neural networks", Journal of biomedical informatics, Vol. 86, pp. 25-32, 2018.