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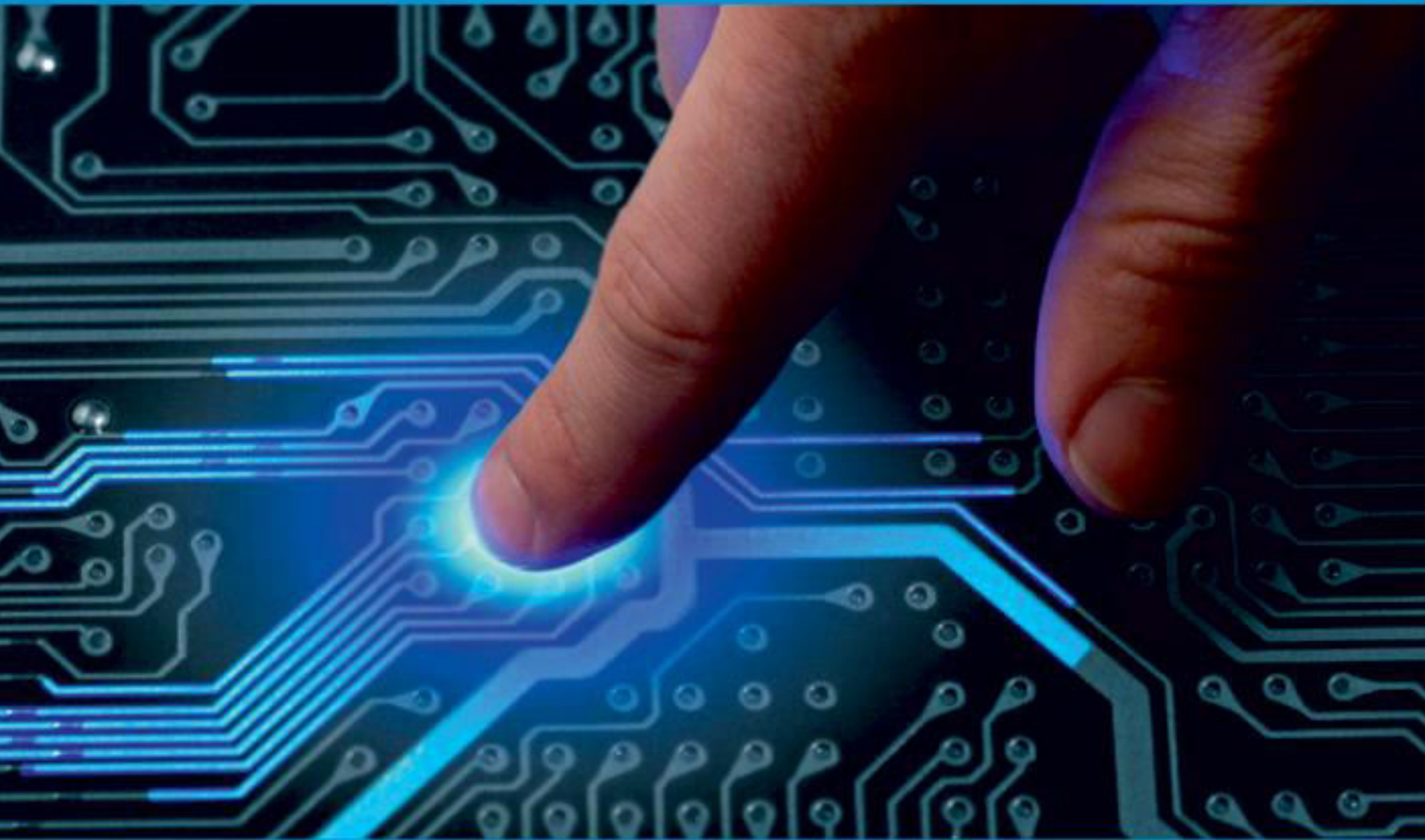

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Artificial Intelligence Framework for Skin Cancer Detection and Classification

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ABSTRACT: In recent days, skin cancer becomes most effected disease of all the types of cancers and it is divided as benign and malignant. In these two types Malignant is recognized as deadliest one while comparing with the non-Malignant skin cancers. It is known fact that Malignant effects more people year by year wise and early treatment are really important for the survival of the patients. Inspection of malignant needs well experienced dermatologists. These people use computer-assisted system early detection of Malignant many works have utilized image pre-processing for the identification of the Malignant at the initial times, which leads to effective treatment using machine learning algorithms. In this way; it is necessary to broaden the span of such essential diagnostic care by arranging efficient frameworks for skin disease classification. Many research papers have utilized image pre-processing for the identification of the Malignant at the initial times, which leads to effective treatment. Proficient dermatologists have set up the ABCDEs (Asymmetrical shape, Border irregularities, Colour, Diameter, and Evolution) as the standardized descriptions to help with visualizing standard features of severe Malignant cases one of the main challenges of classifying harmful skin injuries is due to sheer proportions of varieties over the different skin tones from people of different ethnic backgrounds. The accuracy rate of these models is the challenging task are still facing more challenges for achieving the high accuracy rate, models are to be overcome all the drawbacks of conventional models. Most of the related works are focusing on machine learning based algorithms, but they failed to provide the maximum accuracy and specificity. .Thus, to overcome this problem, the proposed method is implemented with the Artificial intelligence based probabilistic neural network model will be employed for classification mechanism. The k-means clustering is used to segment the image followed by GLCM and DWT based multi-level features are extracted. Thus, the proposed method can be effectively used for classification of Benign and Malignant skin cancers.

KEYWORDS: Benign, Malignant, Pre- Processing, k- means clustering, image segmentation, Feature extraction

I. INTRODUCTION

For the sixteenth century, human cancer was one of the complex diseases which are basically caused by the accumulation of multiple molecular alternations and genetic instability. Prognostic classifications and Current Diagnostic do not reflect the tumour and which is insufficient to create a kind of prediction approach to successful treatment. Most of the presently employed anti-cancer agents do not importantly differentiate between normal and cancerous cells[1]. Additionally, the cancer is often treated and diagnosed too late, here also considered about when the cancer cells have already metastasized and invaded into other parts of the body. Among many sorts of cancer, skin cancers are one of the most common forms of cancer in a human. There are two major sorts of skin cancer, namely Non-Melanoma and Melanoma (Merkel cell carcinomas, squamous cell, basal cell and so on) [1]. Melanoma is one of the most dangerous skin cancers and can be fatal if not treated. In case detect the melanoma in early stages, it is curable highly, yet progressive melanoma is deadly. Therefore, it is well known which means the early treatment and finding of skin cancer can minimize the morbidity. The digital image processing methods are considered widely and accepted in the medical field. An automatic image processing approach normally has different kinds of stages such as the initial image analysing the given image, proper segmentation after that feature extraction and selecting the needed features and finally the lesion recognition. The segmentation process is incredibly significant since it affects the subsequent step precision values. The supervised segmentation is used to vary the different kinds of parameters such as lesion colours, sizes, shapes along with diverse skin textures and types. However, unsupervised segmentation is a well-known different task and different kind of properties. While significant research effort has gone to a different kind of computerized procedure to process the skin image, there are still some drawbacks.

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In recent days, skin cancer has become the most affected disease of all the types of cancers, and it is divided as benign and malignant. These two types of melanoma are recognized as the deadliest one while comparing with the non-melanoma skin cancers [2]. It is a known fact that melanoma affects more people year by year and early treatment is important for the survival of the patients. Inspection of malignant melanoma needs well experienced dermatologists. These people use computer-assisted systems for early detection of melanoma. More algorithms in deep learning models were used for skin cancer diagnosis. The accuracy rate of these models is still facing more challenges. For achieving the high accuracy rate, models are to overcome all the drawbacks of conventional models.

II. RELATED WORK

In computer vision, segmentation refers to 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 analyse. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as colour, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics.

- Thresholding
- Edge finding
- Binary mathematical morphology
- Gray-value mathematical morphology

In the analysis of the objects in images it is essential that we can distinguish between the objects of interest and "the rest." This latter group is also referred to as the background. The techniques that are used to find the objects of interest are usually referred to as segmentation techniques - segmenting the foreground from background. In this section we will discuss two of the most common techniques: thresholding and edge finding and we will present techniques for improving the quality of the segmentation result. It is important to understand that:

1. There is no universally applicable segmentation technique that will work for all images, and,
2. No segmentation technique is perfect.

III. PROPOSED METHOD

A. *Methods used are stated below*

- Image acquisition
- Pre- processing
- Impulse Noise
- Image Segmentation
- Feature extraction
- Classification

Image acquisition

A machine vision system is applied to acquire the skin cancer and wheat images. A wireless IP camera is placed above 20 meters in the cultivation field. This setup captures a video and it was converted into a number of frames using image processing techniques.

Pre processing

Performing this step enhances the quality of the collected photos before they can be subjected to additional examination. Noise is defined as any undesirable information that may readily contaminate photographs. Almost all images and videos have some level of noise that significantly lowers the overall quality of the picture. Difficulty producing different types of noise may be caused by a variety of common causes, including specks of dust on or within the camera's lens, malfunctioning CCD parts in digital cameras, and other factors. It may also arise because of noisy

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sensors or transmission channel faults. A picture that has been damaged by various types of noise is an issue that occurs regularly in the capture and transmission of images. The noise arises from either the noisy sensors or from transmission faults caused by the channel. Listed below are the many sorts of noise that might be encountered. In addition to impulse noise (also known as salt and pepper noise), there is also gradualism (also known as white noise), speckle or multiplication, and periodic noise.

Impulse Noise

The impulse noise is also called salt and pepper noise. It is caused by sharp, sudden disturbances in the image signal. Its appearance is randomly scattered white or black (or both) pixels over the image. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. In image and video processing, images are often corrupted by impulse noise. In this thesis, most popular methods are used to remove impulse noise such as median filter, mean filter and wiener filter. Performances of the median filter, mean filter and wiener filter are evaluated using the peak signal-to-noise ratio (PSNR), which is defined as

$$PSNR = 10 \log_{10} 255^2/MSE$$

Where MSE is the mean squared error (MSE)and defined as

$$MSE = 1/RC \sum_{r=1}^{R} \sum_{c=1}^{C} (s[r,c]-y[r,c])^2$$

Here, s[r,c] and y[r,c] represent the original and the restored versions of a corrupted test image, respectively.

Image Segmentation

Image segmentation is the process of dividing an image into multiple parts. This is typically used to identify objects or other relevant information in digital images. There are many different ways to perform image segmentation, including: Thresholding methods

- Otsu’s method, Color-based Segmentation
- K-means clustering, Transform methods
- Watershed segmentation, Texture methods
- Texture filters,

Feature Extraction

Feature extraction is that of extracting from the raw data, the information, which is most relevant for classification purposes, in the sense of minimizing the within-class pattern variability while enhancing the between-class pattern variability. During the feature extraction process the dimensionality of data is reduced. This is almost always necessary, due to the technical limits in memory and computation time. A good feature extraction scheme should maintain and enhance those features of the input data which make distinct pattern classes separate from each other. At the same time, the system should be immune to variations produced both by the humans using it and the technical devices used in the data acquisition stage.

The most common visual features include colour, texture, shape etc. Most image annotation and retrieval systems have been constructed based on these features. However, their performance is heavily dependent on the use of image features. In this work, texture features are extracted to recognize skin cancer disease and nutrients deficiency.

Classification

Classification is the process by attribute a class label to a set of measurements. Essentially, this is the heart of pattern recognition. Image classification analyzes the numerical properties of various image features and organizes data into categories. Machine learning focuses on prediction, based on known properties learned from the training data. Machine learning algorithms can be classified into two major categories. Non-Supervised learning method, Supervised learning method, In non-supervised learning, the training data given to the learner are unlabeled. It learns to understand and describe the data by finding patterns and structure in data. Clustering partitions a data set into subsets (clusters) so that data in each subset ideally share some common characteristics. Supervised learning a classification divides samples in

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classes using a trained set of previously labeled data. Classification is different from clustering in that it requires 62 that the analyst known ahead of time how classes are defined. The output of classification is discrete. Regression computes new values for a dependent variable based on the values of one or more measured attributes. The output of regression is continuous. Among classification methods, very important classification methods such as KNN-SVM with Gaussian Radial Basis Function (SVM (GRBF)) were used in this thesis.

Texture feature based on GLCM

Texture analysis refers to the characterization of regions in an image by their texture content. Texture analysis attempts to quantify intuitive qualities described by terms such as rough, smooth, silky, or bumpy as a function of the spatial variation in pixel intensities. In this sense, the roughness or bumpiness refers to variations in the intensity values, or gray levels. Using the texture filter functions these statistics can characterize the texture of an image because they provide information about the local variability of the intensity values of pixels in an image. For example, in areas with smooth texture, the range of values in the neighbourhood around a pixel will be a small value; in areas of rough texture, the range will be larger. Similarly, calculating the standard deviation of pixels in a neighbourhood can indicate the degree of variability of pixel values in that region. And the statistics can be explained in the following tabular column.

GLCM creates a matrix with the directions and the distance between the pixels, and then extracts meaningful statistics from the matrix as texture features. GLCM texture features commonly shown in the following.

GLCM is composed of the probability value, it is defined as $P(i,j|d,\theta)$ which expresses the probability of the couple pixels at θ direction and the d interval. When θ and d are determined $P(i,j|d,\theta)$ is shown by $p_{(i,j)}$. Distinctly GLCM is a symmetry matrix its level is determined by the image gray level. Elements in the matrix are computed by the equation shown as the following.

$$p_{(i,j|d,\emptyset)} = \frac{p_{(i,j|d,\emptyset)}}{\sum_i \sum_j p_{(i,j|d,\emptyset)}}$$

GLCM expresses the texture feature according the correlation of the couple pixels Gray level at different positions. It quantificationally describes the texture features. But here mainly four things are considered they are energy, contrast, entropy, and the inverse difference.

Energy:

$$E = \sum_x \sum_y P(x,y)^2$$

It is a gray scale image texture measure of the homogeneity changing reflecting the distribution of the image gray-scale uniformity of the image and the texture.\

Contrast:

Contrast is the main diagonal near the moment of inertia, Which measures the value of the matrix is distributed and images of local changes in the number, reflecting the image clarity and the texture of the shadow depth if the contrast is large then the texture is deeper.

$$I = \sum \sum (x-y)^2 P(x,y)$$

Entropy:

Entropy measures image texture randomness, when the space co-occurrence matrix for all values is equal, it achieved the minimum value; on the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random.

$$S = -\sum_x \sum_y p(x,y) \log p(x,y)$$

Inverse difference:

It measures local changes in image texture number. Its value in large is illustrated that image texture between the different regions of the lack of change and partial very evenly.

Here p(x,y) is the gray level value at the co-ordinate (x,y)

$$H = \sum_x \sum_y \frac{1}{1+(x-y)^2} p(x,y)$$

Then, 2 level DWT is also used to extract the low-level features. Initially on the on the segmented output DWT is applied, it will result the output as the LL1, LH1, HL1 and HH1 bands respectively. Then entropy, energy and correlation features are calculated on the LL band. Then, on the LL output band again DWT is applied, and results the output as LL2, LH2, HL2 and HH2 respectively. And finally, Mean, and standard deviation based Statistical Color features are extracted from the segmented image.

They are.

Mean (μ) =1/N^2 Σ_(i,j=1)^N▒〖I(i,j)〗

Standard Deviation (σ) = √((Σ_(i,j=1)^N▒〖[I(i,j)-μ]^2 〗)/N^2)

Then all these features are combined using array concatenation and results the output as hybrid feature matrix.

For performance metrics:

```
if(isa(A,'logical'))
    X = A;
  else
    X = imbinarize(A);
  end
  if(isa(B,'logical'))
    Y = B;
  else
    Y = imbinarize(B);
  end

 sumindex = X + Y;
  TP = length(find(sumindex == 2));
  TN = length(find(sumindex == 0));
  substractindex = X - Y;
  FP = length(find(substractindex == -1));
  FN = length(find(substractindex == 1));


  Accuracy = (TP+TN)/(FN+FP+TP+TN);
  Sensitivity = TP/(TP+FN);
  Precision = TP/(TP+FP);
  Fmeasure = 2*TP/(2*TP+FP+FN);
  MCC = (TP*TN-FP*FN)/sqrt((TP+FP)*(TP+FN)*(TN+FP)*(TN+FN));
  Dice = 2*TP/(2*TP+FP+FN);
  Jaccard = Dice/(2-Dice);
  Specitivity = TN/(TN+FP);
  End
```

The code above appears to be evaluating the performance of a binary classification algorithm by computing several performance metrics such as Accuracy, Sensitivity, Precision, Fmeasure, MCC, Dice, Jaccard, and Specificity.

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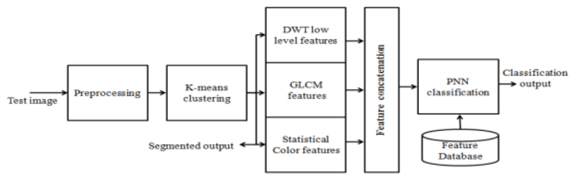
The code starts by checking the data type of input variables A and B. If they are of type logical, the variables are assigned to X and Y, respectively. Otherwise, the variables are binarized using the 'imbinarize' function before being assigned to X and Y.

After that, the code computes the True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) by comparing the sum and subtraction of X and Y. TP represents the number of correct positive predictions, TN represents the number of correct negative predictions, FP represents the number of incorrect positive predictions, and FN represents the number of incorrect negative predictions.

Next, the code computes several performance metrics using the TP, TN, FP, and FN values. Accuracy measures the overall correctness of the classification algorithm, Sensitivity measures the proportion of actual positives that are correctly identified, Precision measures the proportion of predicted positives that are actually positive, Fmeasure is the harmonic mean of Precision and Sensitivity, MCC measures the correlation between the actual and predicted values, Dice is a similarity coefficient that measures the agreement between the actual and predicted values, Jaccard is another similarity coefficient that measures the similarity between the actual and predicted values, and Specificity measures the proportion of actual negatives that are correctly identified.

IV. EXTENSION METHODOLOGY

The proposed research work majorly focusing on detection of following skin cancers such as Malignant and Benign, respectively. The detailed operation of the skin cancer detection and classification approach is presented in figure below



Database training and testing

Database is trained from the collected images of "International Skin Imaging Collaboration (ISIC)" Archive. ISIC is one of the biggest available collections of quality controlled dermoscopic images. The dataset consisted of 15 benign and 15 malignant images. All the images are trained using the PNN network model with GLCM features, statistical and texture features. And random unknown test sample is applied to the system for detection and classification, respectively.

Pre processing

The query image is acquired from image acquisition step, which includes background information and noise. Pre-processing is required and necessary to remove the above-mentioned unwanted portions. The pre-processing stage is mainly used for eliminating the irrelevant information such as unwanted background part, which includes noises, labels, tape and artifacts and the pectoral muscle from the skin image. The different types of noise occurred in the mammogram images are salt and pepper, Gaussian, and speckle and Poisson noise. When noise is occurred in an image, the pixels in the image show different intensity values instead of true pixel values.

So, by choosing the perfect method in the first stage of pre-processing, this noise removal operation will perform effectively. Reduction of the noise to a great extent and avoiding the introduction visual artifacts by the analysis of pixels at various scales, sharpening and smoothing filter denoising efforts to eradicate the noise presented in the pixel, as it conserves the image uniqueness, despite of its pixel satisfied. These filters can effectively detect and remove noise and thin hairs from the image; then we perform top hat transform for removing the thick hairs. Contrast limited adaptive histogram equalization CLAHE is also performed on the skin lesion to get the enhanced image in the spatial domain. Histogram equalization works on the whole image and enhances the contrast of the image, whereas adaptive histogram equalization divides the whole image and works on the small regions called tiles. Each tile is typically 8*8 pixels, and within each tile histogram is equalized, thus enhancing the edges of the lesion. Contrast limiting is applied to limit the contrast below the specific limit to limit the noise.

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Image Segmentation

After the pre-processing stage, segmentation of lesion was done to get the transparent portion of the affected area of skin. On transformation, K-means clustering method is applied to the image to segment the skin lesion area based on thresholding. In K-means clustering algorithm, Segmentation is the initial process of this work, at the cluster centers, cost junction must be minimized which varies with respect to memberships of user inputs. Image segmentation is the process of dividing the image into multiple clusters based on the region of interest presented to detect the skin cancer. Regions of interest are portion of skin images, which are used by radiologists to detect abnormalities like micro classifications (benign and malignant).

K-means clustering is used in the proposed procedure for segmentation to a certain extent than Active counter clustering approach because of its speed of operation with maintaining the highest accuracy. K means clustering procedure combines the properties of jointly possibility and K means clustering approaches as shown in figure 2. Here the membership functions are generated in the probability-based manner to gets better detection. Among those detected tumors, the highest accurate cancer regions considered as ROI. The automatic extraction of ROI is difficult. So, ROIs are obtained through possibility cropping, which are based on location of abnormality of original test images. Here the membership functions are generated in the probability-based manner to gets better detection. Among those detected Cancer regions, the highest accurate Cancer region is considered as ROI.

Feature extraction

Several features can be extracted from the skin lesion to classify the given lesions. We extracted some of the prominent features which help us in distinguishing the skin lesions, those are GLCM based Texture features; DWT based low level features and statistical color features, respectively.

GLCM is a texture technique of scrutinizing textures considering spatial connection of image pixels. The texture of mage gets characterized by GLCM functions through computations of how often pairs of pixels with explicit values and in a particular spatial connection are present in image. GLCM matrix can be created, and then statistical texture features are extracted from the GLCM matrix. GLCM shows how different combinations of pixel brightness values which are also known as grey levels are present in image. It defines the probability of a particular grey level being present in the surrounding area of other grey level.

V. SIMULATION RESULTS

The experiments are done using MATLAB R2018a tool. ISIC is one of the biggest available collections of quality controlled dermoscopic images. For the implementation of the proposed method, spatial domain, and frequency domain of 30 dermoscopic skin lesion images (15-benign and 15-Malignant) have been obtained respectively by applying rotations at different angles. Train images of each label have been used to train the PNN architecture with fifty Epochs, whereas rest twenty percent is used for testing. The features extracted by GLCM, DWT future network are used to train PNN classifier to classify the images into its respective classes. The efficiency of the model can be computed using various performance metrics.From figure 2, it is observed that the proposed method can be effectively detecting the regions of skin cancers, it indicates the segmentation done very effectively compared to the Active contour approach. Here, TEST-1 and TEST 2 images are considered as the benign and TEST-3 and TEST-4 images are considered malignant type images, respectively. For the malignant images, the segmentation accuracy is more.

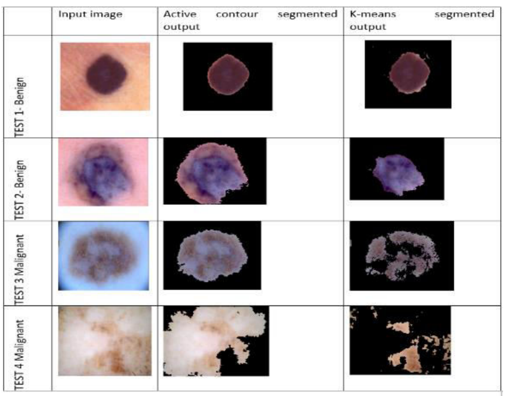

Figure 2 – segmented outputs of various methods

Metric	method	Test 1	Test 2	Test 3	Test 4
Accuracy	PNN-AC	0.9157	0.78099	0.85796	0.47765
	PNN-k means	0.99985	0.99715	0.99999	0.99999
Sensitivity	PNN-AC	0.70588	0.90024	0.9166	0.83857
	PNN-k means	0.99931	0.99198	1	1
F measure	PNN-AC	0.82207	0.68494	0.79395	0.44602
	PNN-k means	0.99965	0.99381	0.99998	0.99998
Precision	PNN-AC	0.98404	0.55275	0.70023	0.30381
	PNN-k means	1	0.99852	0.99997	0.99997
MCC	PNN-AC	0.7869	0.56857	0.70305	0.1835
	PNN-k means	0.99956	0.99198	0.99998	0.99998
Dice	PNN-AC	0.82207	0.68494	0.79395	0.44602
	PNN-k means	0.99965	0.99381	0.99998	0.99998
Jaccard	PNN-AC	0.69789	0.52085	0.65831	0.28702
	PNN-k means	0.99931	0.9877	0.99997	0.99977
Specificity	PNN-AC	0.99564	0.73812	0.83298	0.35685
	PNN-k means	1	0.99956	0.99999	0.99998

Table 1 – performance comparison

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Performance metrics

For evaluating the performance measure the proposed method is implemented with the two types of segmentation methods, they are Active contour (AC) and k-means clustering, respectively. For performing this comparisons Accuracy, Sensitivity, F measure, Precision, MCC, Dice, Jaccard and Specificity parameters are calculated, respectively.

VI. CONCLUSION AND FUTURE WORK

This project presented a computational methodology for detection & classification of skin cancer from MRI images using PNN based deep learning-based approach. Here, Gaussian filters are utilized for pre-processing, which eliminates any unwanted noise elements or artifacts innovated while image acquisition. Then K-means clustering segmentation is employed for ROI extraction and detection of cancerous cells. Then GLCM, DWT based method was developed for extraction of statistical, color and texture features from segmented image respectively. Finally, PNN was employed to classify the type of cancer such as either benign or malignant using trained network model. Thus, upon comparing with state of art works, we conclude that PNN is better than conventional SVM method. In future, this work can be extended by implementing a greater number of network layers into the PNN and can also be applied for other type of benign and malignant cancers.

REFERENCES

[1] Kadampur, Mohammad Ali, and Sulaiman Al Riyaee. "Skin cancer detection: applying a deep learning-based model driven architecture in the cloud for classifying dermal cell images." Informatics in Medicine Unlocked 18 (2020): 100282.

[2] Munir, Khushboo, et al. "Cancer diagnosis using deep learning: a bibliographic review." *Cancers* 11.9 (2019): 1235

[3] Akram, Tallha, et al. "A multilevel features selection framework for skin lesion classification." *Human-centric Computing and Information Sciences* 10 (2020): 1-26.

[4] Marka, Arthur, et al. "Automated detection of nonMalignant skin cancer using digital images: a systematic review." *BMC medical imaging* 19.1 (2019): 21.

[5] Gaonkar, Rohan, et al. "Lesion analysis towards Malignant detection using soft computing techniques." *Clinical Epidemiology and Global Health* (2019).

[6] Hekler, Achim, et al. "Superior skin cancer classification by the combination of human and artificial intelligence." *European Journal of Cancer* 120 (2019): 114-121.

[7] Hekler, Achim, et al. "Superior skin cancer classification by the combination of human and artificial intelligence." European Journal of Cancer 120 (2019): 114-121.

[8] Rajasekhar, K. S., and T. Ranga Babu. "Skin Lesion Classification Using Convolution Neural Networks." Indian Journal of Public Health Research & Development 10.12 (2019): 118-123.

[9] Iyer, Vijayasri, et al. "Hybrid quantum computing based early detection of skin cancer." Journal of Interdisciplinary Mathematics 23.2 (2020): 347-355.

[10] Roslin, S. Emalda. "Classification of Malignant from Dermoscopic data using machine learning techniques." Multimedia Tools and Applications (2018): 1-16.

[11] Moqadam, SepidehMohammadi, et al. "Cancer detection based on electrical impedance spectroscopy: A clinical study." Journal of Electrical Bioimpedance 9.1 (2018): 17-23.

[12] Hosny, Khalid M., Mohamed A. Kassem, and Mohamed M. Foaud. "Skin cancer classification using deep learning and transfer learning." 2018 9th Cairo International Biomedical Engineering Conference (CIBEC). IEEE, 2018.

[13] Dascalu, A., and E. O. David. "Skin cancer detection by deep learning and sound analysis algorithms: A prospective clinical study of an elementary dermoscope." EBioMedicine 43 (2019): 107-113.

[14] M. Vidya and M. V. Karki, "Skin Cancer Detection using Machine Learning Techniques," 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, 2020, pp. 1-5, doi: 10.1109/CONECCT50063.2020.9198489.

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