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EARLY DETECTION OF MELONAMA IN SKIN CANCER USING PROBABILISTIC NEURAL NETWORKS

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Abstract

Skin cancer can be both benign and malignant, has emerged as the most common type of cancer in recent years. When compared to non-malignant skin cancers, malignant skin cancers are known to be the more lethal of these two types. It is well known that the number of cases of cancer cases rises annually, and that patients' chances of survival greatly depend on receiving treatment as soon as possible. Expert dermatologists are required for the examination of cancerous growths. These people make use of computer-assisted systems for early cancer detection. In order to advance the identification of melanoma, a prototype system that can differentiate between different types of skin cancer symptoms is being developed. This study will assist patients in preventing melanoma at an early stage. In this Paper we proposes efficient Classification and Extraction of Pigmented Skin lesion such as that of melanoma using Probabilistic Neural Networks. This method, which uses automation and image processing to diagnose and treat skin cancer patients, is particularly helpful in reducing treatment costs and improving the pace at which pigmented skin lesions, such those found in melanoma, may be identified. Physical therapists in remote areas may find this method useful in detecting melanoma early on. Cost and time consumption are the primary mottos.

Keywords: Malignant Skin Cancer, Melanoma, Image Segmentation, Probabilistic Neural Networks

I. INTRODUCTION

Human cancer was considered to be one of the complicated diseases of the sixteenth century, mostly due to genetic instability and the accumulation of numerous molecular alternations. The tumor is not reflected in prognostic classifications or current diagnostics, which is insufficient to develop a successful treatment plan that can be predicted. The majority of anti-cancer medications now in use do not significantly distinguish between healthy and malignant cells. [1]. Furthermore, cancer is frequently discovered and treated too late, taking into account the fact that the cancer cells may have already spread to other parts of the body at this point. Skin malignancies are among the most prevalent types of cancer in humans among all cancer types. Skin cancer is classified into two main types: non-melanoma and melanoma [2]. One of the most serious skin tumors, melanoma can be lethal without treatment. Early detection of melanoma increases the likelihood of cure; however, progressing melanoma is fatal. Because of this, it is widely recognized that detecting and treating skin cancer early on can reduce its morbidity. The technologies for digital image processing are widely regarded as part of the medical field's system [3]. An automatic image processing approach often consists of several stages, such as initial picture analysis, correct segmentation, feature extraction, feature selection, and lesion recognition. Because segmentation impacts the precision values of the subsequent steps, it is quite important [4]. Supervised segmentation is employed to adjust many parameters, including lesion colors, sizes, and forms, as well as distinct skin textures and types. On the other hand, unsupervised segmentation is a well-known problem with distinct features. Even though a lot of study has gone into developing a new digital method to process the skin picture, there are still certain shortcomings. Skin cancer is currently the most frequent condition, with a 40% increase. Suspective cases of skin cancer are commonly biopsied, which is a painful process for the patient and sluggish in producing diagnostic results [5]. Furthermore, a large percentage of unnecessary

biopsies are performed. The process of identifying a skin texture or issue by symptoms, signs, and the various types of diagnosis process results is done by the skin cancer image processing system. More than half of all malignancies are skin cancers, which are malignant tumors that develop in skin cells.

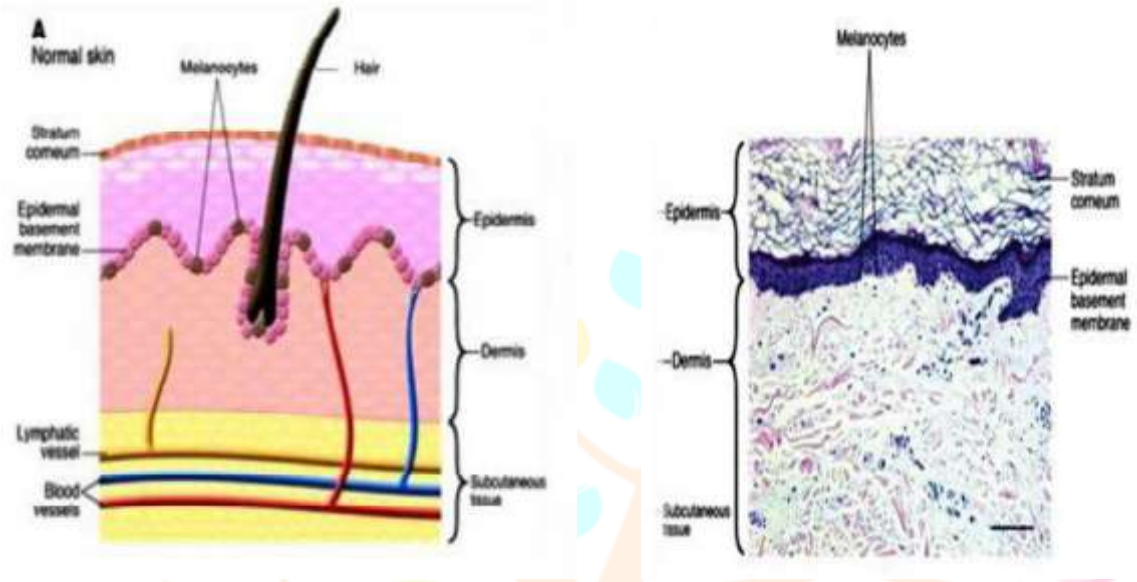

Figure 1: Skin Structure: Epidermis, Dermis and, Hypodermis Layer

II IMAGE SEGMENTATION

Image segmentation, as used in computer vision, is the division of a digital image into several parts. Segmentation is to transform an image's representation into something more understandable and straightforward to examine. Usually, image segmentation is used to find boundaries and objects in images. More specifically, image segmentation is the process of giving each pixel in an image a label so that those pixels share certain visual traits. A collection of contours that are retrieved from the image or a collection of segments that together cover the full image are the outcomes of image segmentation. When it comes to a certain attribute or computed property, like color, texture, or intensity, every pixel in a region is comparable. The same parameters show considerable differences between adjacent regions. Being able to differentiate between the things of interest and "the rest" is crucial for the analysis of objects in photographs. The methods used to separate the foreground from the background and locate objects of interest are commonly referred to as segmentation techniques. Two of the most popular segmentation techniques—thresholding and edge finding—as well as methods for raising the caliber of the segmentation output are covered in this section. It is imperative to comprehend that there exists no segmentation technique that is ideal or that can be used universally to all photos.

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Figure 2: Image Segmentation

Theresholding

This method is predicated on a straightforward idea. The brightness threshold is a parameter that is selected and applied in the following manner to the image a [m, n]:

$$\begin{cases} \text{If } a[m,n] \geq \theta & a[m,n] = object = 1 \\ \text{Else} & a[m,n] = background = 0 \end{cases}$$

The algorithm in this iteration is predicated on the idea that we are interested in bright items against dark backgrounds. In the case of dark objects against light backgrounds, we'd use:

$$\begin{cases} \text{If } a[m,n] < \theta & a[m,n] = object = 1 \\ \text{Else} & a[m,n] = background = 0 \end{cases}$$

Using a threshold that is selected apart from the picture data is one option. A consistent threshold of 128 on a scale of 0 to 255 might be adequate if it is known that one is working with extremely high contrast photos where the objects are very dark and the background is homogeneous and very light. By accuracy, we mean minimizing the amount of incorrectly categorized pixels. Usually, we select the threshold based on the brightness histogram of the area or picture we want to segment. Figure 3 displays an image together with the corresponding brightness histogram.

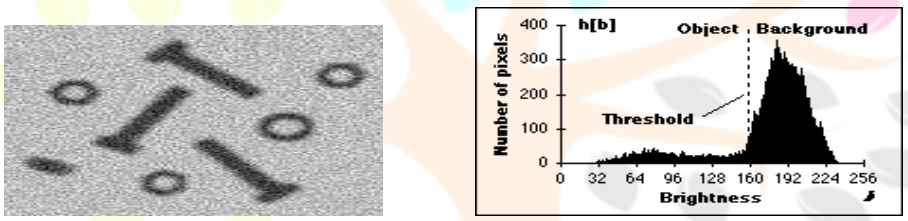


Figure 3: Thresholding

Edge Finding

When a picture is threshold, all the pixels that theoretically belong to the object or objects of interest are extracted. Finding the pixels that correspond to the object borders is an alternative of doing this. Edge finding approaches are methods that are focused on achieving this objective. The primary difficulty with edge finding methods is identifying processes that result in closed contours surrounding the objects of interest. This can be done for objects with a very high signal-to-noise ratio (SNR) by computing the gradient and applying an appropriate cutoff. Figure 4 provides an illustration of this. Using the zero crossings produced in an image's Laplacian is a more contemporary method of addressing the issue of edges in noisy images. The reasoning begins with the step function model of an ideal edge, which is then blurred by an Out of Focus to yield the outcome displayed in Figure 5.

Figure 4: Edge finding based on the Sobel gradient

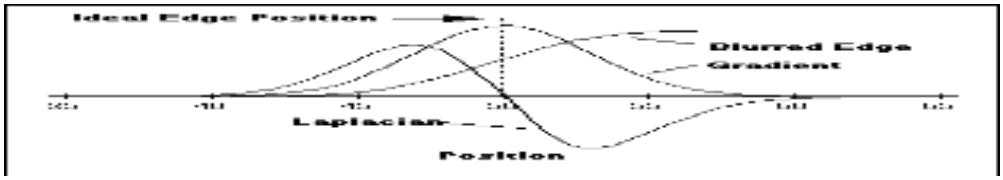


Figure 5: Edge finding based on the zero crossing

III PROPOSED METHOD

The proposed study will primarily concentrate on the detection of the ensuing skin cancer types, such as benign and malignant, respectively. Figure 6 illustrates the methodical execution of the skin cancer detection and categorization strategy.

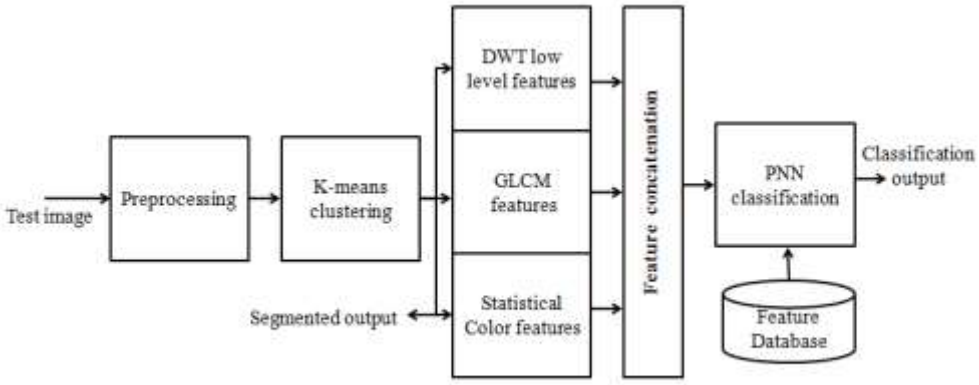


Figure 6: Proposed Approach of Skin cancer detection and classification

Database Training and Testing

The photos gathered from the "International Skin Imaging Collaboration (ISIC)" Archive are used to train the database. One of the largest collections of high-quality, controlled dermoscopic images is ISIC. There were 15 benign and 15 cancerous pictures in the collection. The PNN network model is used to train all of the images using GLCM, statistical, and texture features. Additionally, the system is used to apply a random unknown test sample for classification and detection, respectively.

Preprocessing

The query image is obtained during the image acquisition process, which also gathers noise and background information. Pre-processing is essential to removing the undesirable elements mentioned above. Pre-processing is mostly used to eliminate unnecessary information from the skin image, including labels, noise, tape, artifacts, and unwanted background components like the pectoral muscle. The pre-processed image is shown in Figure 7.a. Hue Intensity Saturation (HIS) color conversion is also used to map the same intensity pixels of skin lesions, as seen in Figure 7(b).

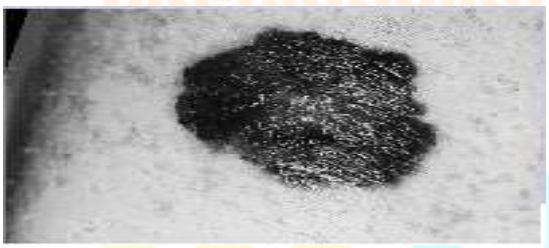


Figure 7(a): Preprocessed image of Skin Lesion

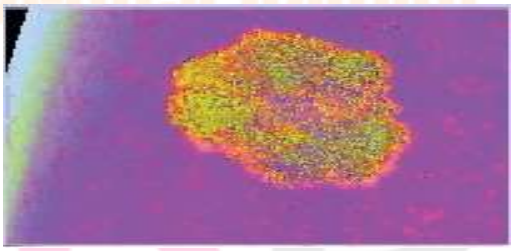


Figure 7(b): HIS Image of Skin Lesion

Image Segmentation

Following the pre-processing phase, the lesion was segmented to extract the transparent skin region that was impacted. Following modification, the image is subjected to the K-means clustering approach, which uses thresholding to segment the skin lesion region. Segmentation is the first step in the K-means clustering algorithm. At the cluster centers, cost junction—which changes depending on the memberships of user inputs—must be reduced. The method of splitting an image into several clusters according to the region of interest displayed in order to identify skin cancer is known as image segmentation. Radiologists utilize regions of interest, which are sections of skin scans, to find anomalies such as micro classifications

Because K-means clustering operates quickly while preserving the best accuracy, it is utilized more in the suggested segmentation technique than the Active counter clustering approach. Figure 8 illustrates how the clustering technique, denoted by K, combines the jointly possible and K means clustering approaches. To improve detection, the

membership functions are constructed in this case using a probability-based approach. The most accurate cancer locations among those diagnosed tumors were deemed to be ROI. It is challenging to extract ROI automatically. Hence, ROIs are acquired by possible cropping, which is predicated on the original test images' abnormality location. To improve detection, the membership functions are constructed in this case using a probability-based approach. The most accurate cancer location among those identified is regarded as ROI.

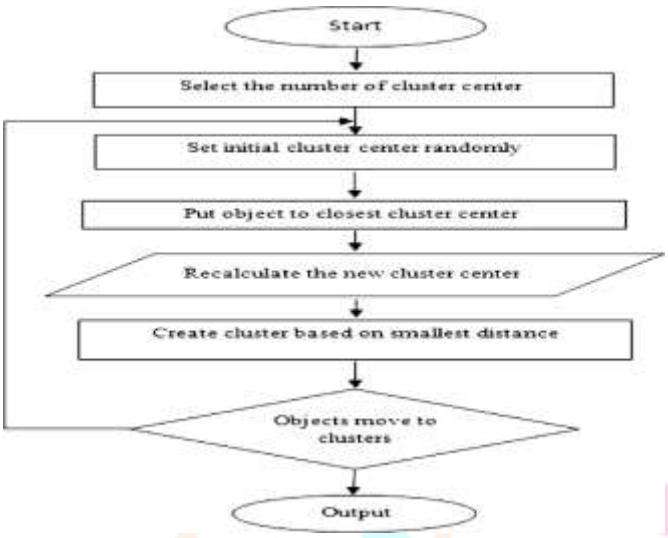


Figure 8: K-means clustering

Feature Extraction

To categorize the specific lesions, a number of characteristics can be taken from the skin lesion. A few of the key features that aid in the differentiation of skin lesions were extracted. These features include statistical color features, DWT-based low level features, and texture features based on GLCM. A texture approach called GLCM examines textures by taking into account the spatial relationships between image pixels. By calculating the frequency of pairs of pixels with defined values and in a certain spatial link within an image, GLCM functions characterize the texture of the picture. It is possible to generate a GLCM matrix and then extract statistical texture features from it. GLCM illustrates the many pixel brightness value combinations & also referred to as grey levels that are present in an image. It indicates the likelihood that a specific gray level will exist in close proximity to another grey level

In this work, the three-color spaces—RGB, CIE L*u*v, and YCbCr—images are first processed to extract the GLCM. Next, as illustrated in figure 8, the GLCM matrix is computed in four directions: 135 degrees, 90 degrees, 45 degrees, and 0 degrees. Let a, b represent the number of rows and columns in the matrix, respectively, and let Sa represent the recorded probability value for the cell (a, b). The number of gray levels in the image is represented by 'N' in these calculations. From these matrices, a number of textural properties can be recovered; these extracted features are displayed in the following equations:

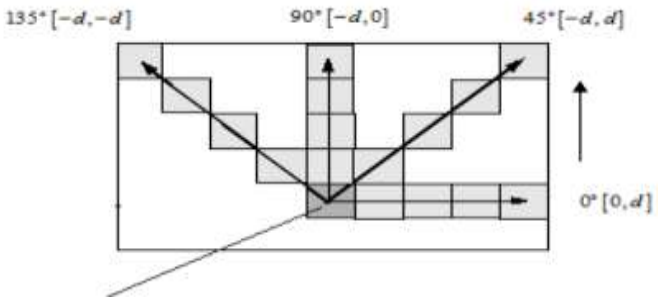


Figure 8: Orientations and distance to compute GLCM

Classification

Many different problem categories, including economics, medicine, engineering, geology, physics, and biology, have seen successful applications of neural networks. Neural networks hold attention from a statistical perspective due to its

potential applications in prediction and classification issues. A technique called Probabilistic Neural Network was created by simulating the newborn neural network. For the purpose of efficiently carrying out the classification function, the neurons are coupled in the predetermined design. The weights of the neurons are determined by the hybrid properties. Next, its distinctive hybrid properties are used to identify the relationships between the weights. The number of weights determines the proposed network's layer levels. The architecture of Probabilistic Neural Networks is shown in Figure 9. For classification, PNN essentially consists of two stages: testing and training. The layer-based design will serve as the basis for the training procedure. The mapping operation on the input dataset is carried out by the input layer, and the hybrid features of this dataset are classified into weight distributions

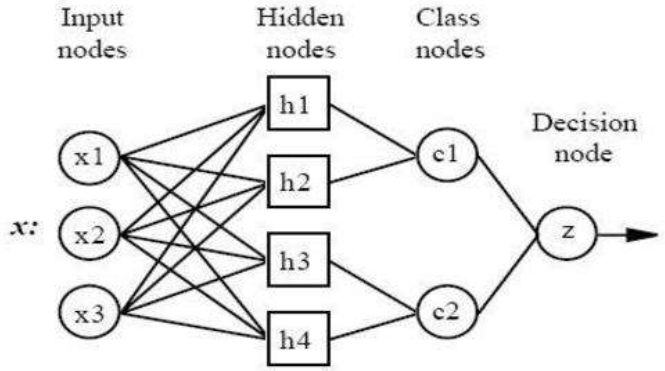


Figure 9: Layered architecture of PNN model

There are four weighted hidden layers in the PNN architecture. Class node activation layer and decision normalization layer come after the first convolution 2D hidden layer of the network, which receives 224 * 224 * 3 pixel skin lesion images and applies 96 11×11 filters at stride 4 pixels. Next, the two levels of the class nodes concealed layer implemented the classification process. The information about the normalcy and anomalies of the characteristics of skin cancer is stored in the two hidden layer levels. It is classified as either normal or pathological based on the segmentation criteria. In the output layer, these two levels are represented as labels. Once more, the hidden layer holds the weights for benign and malignant cancer in the second stage of the hidden layer, as well as the abnormal cancer types individually. In a similar vein, the output layer likewise maps these benign and malignant weights as labels. In order to test the hybrid characteristics of the test image, they are applied during the classification stage. It will operate according to the maximal feature matching criteria using the Euclidean distance method. The picture is categorized as having normal skin if the feature match happened with hidden layer 1 label. An image is classed as benign impacted cancer if the feature match with hidden layer C1 labels with highest weight distribution occurs. An image is characterized as malignant impacted cancer if a feature match with hidden layer C2 labels with minimal weight distribution occurs.

IV RESULTS AND DISCUSSION

To conduct the experiments, the MATLAB R2018a tool is used. One of the largest collections of high-quality regulated dermoscopic images available is that of the International Skin Imaging Collaboration (ISIC). The proposed method has been implemented by using rotations at different angles to acquire the spatial domain and frequency domain of 30 dermoscopic skin lesion images (15-benign and 15-Malignant), respectively. Twenty percent of the train images for each label are used for testing, and the remaining fifty epochs are used to train the PNN architecture. The PNN classifier is trained using the characteristics retrieved by the GLCM and DWT future networks in order to categorize the images into the appropriate classes. Many performance metrics can be used to calculate the model's efficiency.

As seen in Figure 10, the suggested method is capable of accurately identifying the areas where skin malignancies are present. This is because the segmentation was carried out more skillfully than with the Active contour approach. In this case, the photos from TEST-1 and TEST-2 are regarded as benign types, while the images from TEST-3 and TEST-4 are regarded as malignant types. The segmentation accuracy is higher for the pictures that are malignant.

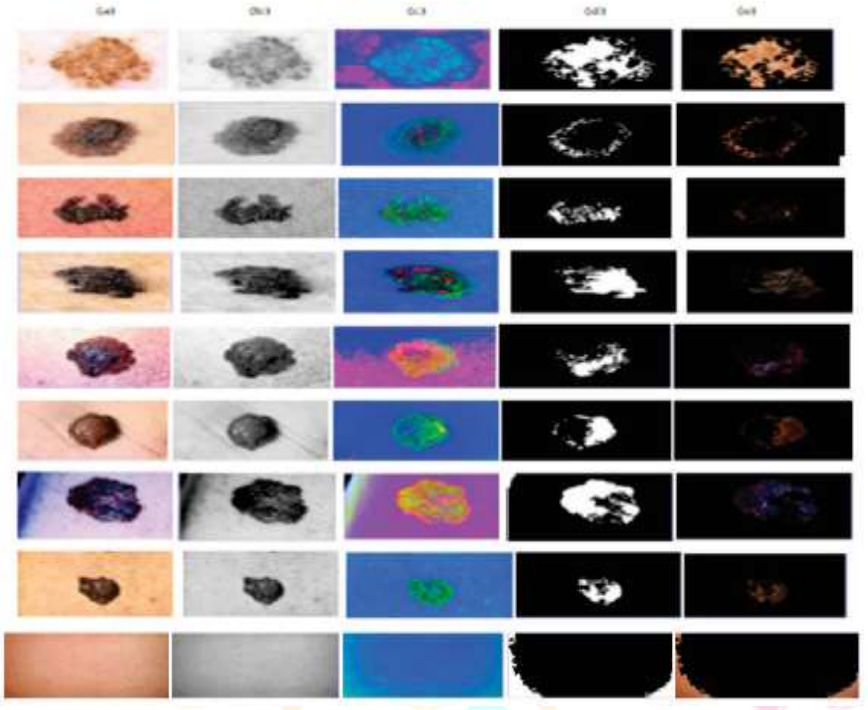


Figure 10: Segmented output images of various methods

Performance metrics

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

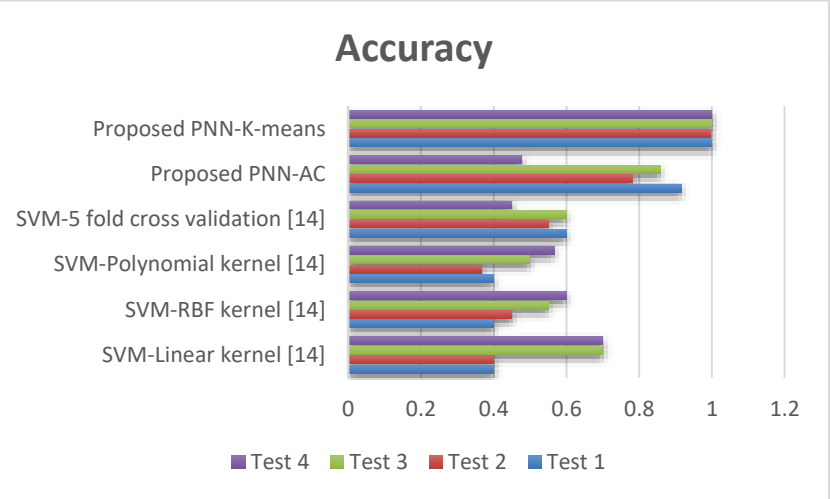
Table 1: Performance comparison

The two segmentation methods used in the suggested method's implementation they are Active contour (AC) and k-means clustering, respectively & they are used to evaluate the performance measure. The following parameters are calculated for this comparison

Table 1 and Figure 10 demonstrate that, in comparison to the Active counter technique, the suggested K-means clustering method with PNN provides the best performance across all criteria.

Method	Test 1	Test 2	Test 3	Test 4
SVM-Linear kernel [14]	0.4	0.40	0.7	0.7
SVM-RBF kernel [14]	0.4	0.45	0.55	0.6
SVM-Polynomial kernel [14]	0.4	0.3667	0.50	0.5667
SVM-5 fold cross validation [14]	0.6	0.55	0.60	0.45
Proposed PNN-AC	0.9157	0.78099	0.85796	0.47765
Proposed PNN-K-means	0.99985	0.99715	0.99999	0.99999

Table 2: Accuracy Comparison



As can be shown from Table 2, the suggested approach outperforms other SVM kernels [14] including SVM-Linear, RBF, Polynomial, and 5-fold cross validation in terms of accuracy for both benign and malignant diseases.

V CONCLUSION

This paper proposed a deep learning-based Probabilistic Neural Networks (PNN) based computational algorithm for the identification and classification of skin cancer using MRI images. Here, pre-processing is done using Gaussian filters to remove any extraneous noise or artifacts that were introduced during the image acquisition process. Then, ROI extraction and cancer cell detection are accomplished using K-means clustering segmentation process. Then, for the purpose of extracting statistical, color, and texture features from segmented images, GLCM and DWT based methods were created. Lastly, a trained network model was used to categorize the type of cancer as either benign or malignant using PNN. Therefore, after comparing with state-of-the-art works, we find that PNN outperforms the traditional SVM approach. By adding more network layers to the PNN in the future, this technology can be expanded and used to treat other kinds of cancer, both malignant and benign.

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