Method to Enhance Classification of Skin Cancer Using Back Propagated Artificial Neural Network

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Abstract. Skin cancer is one of the kinds of cancer that leads to millions of deaths of human beings. Early identification and appropriate medications for new harmful skin malignancy cases are fundamental to guarantee a low death rate as the survival rate. Most of the related works are focusing on machine learning-based algorithms, but they provide the maximum accuracy of and specificity. In the preprocessing stage, sharpening filter and smoothening filters are used to remove the noise along with enhancement operations. Then Otsu's segmentation used for efficient detection of the region of skin cancer. Finally, to achieve the maximum accuracy for classification back-propagated based artificial neural network (BP-ANN) developed for the categorization of skin cancer with the spatially gray level dependency matrix (SGLD) features. The suggested research work can be effectively used for the organization of various Benign and Melanoma skin cancers.

Keywords: Back-propagattion · Artificial neural network · Spatially gray level dependency matrix · Support vector matrix

1 Introduction

In recent days, skin cancer becomes the most affected disease among different types of cancers, and it is divided as benign and malignant. In these two types, melanoma is recognized as deadliest one while comparing with the non-melanoma skin cancers. It is a known fact that melanoma affects more people a year by year wise and early treatment is important for the survival of the patients. Inspection of malignant melanoma needs well-experienced dermatologists. These people use a computer-assisted system early detection of melanoma. In deep learning various procedure prototypes were used for the diagnosis of a skin cancer diagnosis. Many research papers have utilized image preprocessing for the identification of melanoma at the initial times, which leads to effective treatment. In [1,22], authors have utilized image preprocessing for the identification of melanoma at the initial times, which leads to effective treatment. Recently, new activities in

the improvement of CNN have allowed computers and beat dermatologists in skin cancer identification activities.

The remainder of the broadside is structured in Literature survey conducted for paper is covered in Sect. 2. Section 3 covers the suggested melanoma detection method while Sect. 4 describes the environment in which experiments were conducted. Finally, Sect. 5 has remarks that conclude the outcomes and draw inferences from the presented research work.

2   Literature Survey

In recent years artificial intelligence has gained popularity in research for their abilities to predict patterns. They have been applied to many different fields including disease detection [10,30,35,36,43] and classification [9,12,26,45], elderly care [20,21] and fall detection [4,5,33], anomaly detection [7,13,48,49], biological data mining [32,34], cyber security [28], earthquake prediction [2,3], financial prediction [37], safeguarding workers in workplaces [22], text analytics [39,46], and urban planning [23]. Related work about skin image processing and their multiple applications using different kinds of methods and approaches. It also describes different approaches used in the skin cancer identification methodology which is used to detect tuberculosis utilizing technical and medical approaches. Through the elaborate survey is the motivation for the present suggested work.

2.1   Filter and Adaptive Histogram Technique

The adaptive histogram equalization technique used for preprocessing operation. In this work use novel classification and segmentation of skin lesions [34]. The main purpose through this work is a skin cancer identification system with a minimum error by selecting the proper approach in every stage. The standard digital camera is used for capturing the skin lesion image is shows the high screening process of lesion images. The combination of an analytical method and segmentation method aims to enhance these two approaches to create an interface for assist dermatologists in the diagnostic process [32]. The initial step in this work, a series of preprocessing is executed to unwanted structures and removes noise from the given image. Then, an automatic segmentation method traces the skin lesion. Send step is feature extraction is done by using ABCD rule which used to calculate the Total Dermoscopy score.

2.2   Gaussian Method

The segmentation processing of Magnetic Resonance Images (MRI) by utilizing the Unsupervised Neural Network Algorithm (UNNA) [1]. Here considering two different kinds of problems: such as the trained network takes a long time to obtain the Desired Output. Another one that has obtained results from the training process is not correct which contains a lot of noise as a result of the

training process. Thus, in this work employed the2D Discrete Wavelet Transform (DWT) learned Patterns for denoise operation (noise removal or reduction) by processing entire the outcomes from the activity of the segmentation of MRI. The UNNA like Kohonen Network considering the outcome image and the trained process is findings of the given original images. The quality of the image by utilizing the de-noising and resolution concepts such as wiener filter, median filter, average filter, discrete wavelet transform, and the dual tree-based complex wavelet transform approach.

The different preprocessing methods for detecting the lesions and microcalcification from the mammogram image [29]. These preprocessing methods eliminate the unwanted noise present in the input image which is implemented in the MATLAB tool. Then the accuracy of the preprocessing methods has been validated using 30 different mammogram image and the efficiency is examined using the peak signal to noise ratio.

Enhancing the quality of the images by applying the filtering and resolution methods such as median, average, and wavelet filters [14]. These filters estimate the neighboring pixel value for efficiently estimating the new brightness values. Also, these filters maintain the quality of the edge and contour information. Then the performance of the system is analyzed using the peak to signal ratio metrics. These resolution based preprocessing methods improves the quality also enhance the classification accuracy efficiently.

2.3 Segmentation Techniques

Melanoma is a sort of dangerous skin disease; it can be diagnosed only in its early stage but using the normal conventional dermatological approach is a difficult one. An image processing approach by using an efficient segmentation algorithm named a radial search method to obtain the truth of the lesion region in dermoscopy skin images [16]. DL – especially its different architectures – has contributed and been utilized in the mining of biological data pertaining to those three types, a meta-analysis has been performed and the resulting resources have been critically analysed. Focusing on the use of DL to analyse patterns in data from diverse biological domains, this work investigates different DL architectures' applications to these data.

The melanoma skin cancer by using the Otsu thresholding which is used to segments the lesion from the whole image [40]. Further segmentation is done by using a Boundary tracing algorithm. After removing the features from the lesion, the classification process is done by using the Stolz algorithm stage.

The skin-tone regions with the help of edge detection and color spaces in green red channels [14]. The prominent feature of the face is extracted by using wavelet approximations. The experimental results obtained the enhanced False Acceptance Rates (FAR) over either utilizing a grayscale image for segmentation and which algorithm not using any kinds of edge detection.

2.4   Artificial Neural Network Based Techniques

The ANN-based Classification methodology utilizing Artificial Intelligence and Image processing approach for early diagnosis [14]. In this work dermoscopy image of skin cancer is taken for analysis using Computer-Aided Classification, and it is considered different kinds of image enhancement and pre-processing. The 2D Wavelet transform is a well-known Feature Extraction approach is used in this work. These features are feed into as input as in ANN Classifier. It classifies the given data set into non-cancerous or cancerous.

The automatic cancer detection process by utilizing the effective image segmentation process [42]. Before segmenting the image, the noise present in the image should be eliminated by converting the RGB images into the Grayscale image. Then the region growing method has been applied to the noise removed image which combining a similar gradient value based on the image intensity constraints. From the segmented image the affected region related features are calculated which is fed into the supervisor classifier to analyze cancer effectively.

The tumor region by utilizing the fuzzy c means based support vector machine [31]. Initially, the MRI image neighboring pixel value has been analyzed and the input is labeled by using the Fuzzy C - Means method. From the input vectors, the membership function is applied and the affected region is efficiently segmented by using the support vector machine. Then the suggested FCM with Support Vector Machine based segmentation methods has been analyzed using the quadratic kernel function and the non-linearity approach. Thus the suggested method enhances the segmentation process which used to achieve the enhanced results while classifying the segmented region. Finally, the performance of the system is compared with the silhouette method, fuzzy entropy, fuzzy partition coefficient methods.

2.5   Different Feature Extraction Methods

The different feature extraction methods for identifying cancer were elaborated [17]. The author examined skin cancer detection using the computer-aided diagnosis process. The biopsy method is known as the Conventional diagnosis method is used for the skin cancer detection process. In this work utilize a neural network (NN) system as promising modalities for the skin cancer detection process. This work involves different stages of detection which contain a collection of Dermoscopic images, feature extraction utilizing GLCM and classification utilizing ANN, segmenting the images utilizing Maximum Entropy Threshold, filtering the images for removing noises and hairs, It classifies the given data set into the non-cancerous or cancerous image. Cancerous images are classified as non-melanoma and melanoma skin cancer. The identifying techniques utilize Artificial Intelligence and Image processing methods in this paper were projected [11]. The dermoscopy image is taken and then the different pre-processing operation is done for image enhancement and noise removal. After that, the image is fed into the segmentation process utilizing Thresholding.

In this working diagnosis the psoriasis skin disease [44]. This suggested system gives promising results in terms of finding the generalization face. Extracting the shearlet features from the ultrasound cancer image for detecting the normal and abnormal tissues in the affected part. The shearlet transform analyzes the image and the texture metrics are analyzed in the high dimensional way. The extracted features are classified by applying the different classifiers such as the support vector machine, ad boost technique. The extracted features are compared with the different feature extraction techniques such as the contourlet, curvelet, and GLCM approach. The performance of the suggested system is analyzed using the experimental results in terms of accuracy, sensitivity, specificity, predictive values.

2.6   Feature Selection Techniques

Automatic detection of cancer by selecting the optimal feature set from the various Features [47]. During the feature selection process, the features are ranked and the best features are selected using the wrapper approach. Then the selected features are fed into the nearest neighbor classifiers which classify cancer into the benign and malignant. Thus, the suggested system efficiently effectively classifies the tumors.

Analyzing the various feature selection methods such as information gain, gain ratio, best-first search algorithm, chi-square test, recursive feature elimination processes, and the random forest approach [16]. These features select the optimal features from the set features such as the texture, shape, color, and other spectral features. The selected features reduce the dimensionality of the feature set which is fed into the different machine classifiers for identifying the normal and abnormal tissues. Thus, the optimal features ensure efficient results with minimum time complexity.

2.7   Machine Learning Techniques

In this work use the soft computing techniques for analyzing the skin lesion image [41]. Here differentiate the melanoma skin lesions is done by using ABCD and this approach is also done the preprocessing operation and finally, the optimization is done by soft computing operation. The author shows better accuracy in terms of diagnosing melanoma. An intelligent automated approach for identifying the different sorts of skin lesions utilizing machine learning procedures.

Initially, local information is getting over the Local Binary Pattern (LBP) on various kinds of scales, and GLCM at different angles has been mined as a kind of texture feature. Typically, these features are robust because of scale rotation invariant property of GLCM features and invariant property of LBP. The Global information of altered color channels has been integrated through four various moments mined in six different color spaces. Thus, a merged hybrid texture color and local as global features have been recommended to categorize the nonmelanoma and melanoma. The SVM has been utilized as a classifier to classify non-melanoma and melanoma.

The mined feature parameters are utilized to categorize the image as Melanoma cancer lesion and Normal skin. The automatic skin detection process after an initial camera calibration and basically, the test individuals are taken from the human sampling [18]. A scaling is implemented on the work data, before employing the distance that confirms better results than preceding works. In this work use the TSL color space and also successfully utilized, where undesired effects are minimized, and the Gaussian model shows the better skin distribution process considering other color spaces. Additionally, utilizing an initial filter, generally, huge parts of effortlessly distinct non-skin pixels, are eradicated from further processing. Grouping and analyzing the resulting features from the discriminator progresses the ratio of precise detection and minimize the small nonskin region existent in a common complex image including interracial descent persons, Caucasian, background, African, and Asiatic. Also, this approach is not limited to grouping, size, or orientation candidates.

The skin disease utilizing skin image texture analysis and by comparing the test image to reference images or defined images [15]. The matching of reference and test images compared that get the skin diseases percentage in the obtained skin texture image. The classification detection process by extracting only the specified features such as shape, intensity, and histogram values. The captured images are processed by applying the gamma correction process. The extracted methods are categorized into support vector machine which classifies into the malignant and benign. The performance of the system is analyzed using the different feature extraction methods.

2.8   Digital Image Utilizing Technique

The image processing approaches such as a fuzzy inference system and a Neural Network (NN) system were utilized in this work as promising modalities for the detection of various sorts of skin cancer [8]. Extracting the shearlet features from the ultrasound cancer image for detecting the normal and abnormal tissues in the affected part. The Shearlet transform analyzes the image and the texture metrics are analyzed in the high dimensional way. The extracted features are classified by applying the different classifiers such as the support vector machine technique.

The extracted features are compared with the different feature extraction techniques such as the contourlet, curvelet, and GLCM approach. The performance of the suggested system is analyzed using the experimental results in terms of accuracy, sensitivity, specificity, predictive values. Hierarchal Neural Network gets 90.67% while utilizing the neuro-fuzzy system is get 91.26% and NN sensitivity is 95% and specificity is 88% [38]. At the same time, the skin diagnosis system using the neuro-fuzzy system is getting 89% of specificity and 98% sensitivity.

The optical spectroscopy and a multi-spectral classification scheme utilizing SVM to assistance dermatologists in the diagnosis of malign, benign, and normal skin lesions [19]. Initially, in this works show effective classification with 94.9% of skin 45 lesions from normal skin in 48 patients depends on the 436

features. The various classifiers involved in the cancer recognition process which is explained as follows. There are several classification techniques like Bayesian Classifiers, Hidden Markov Model, Support Vector Machine, Self-Organization Map, Fuzzy based Approach, and Neural Networks are used to analyze the different type of cancer. The traditional telemedicine across the world and this study focus on modeling a designing a system and here initially collate past Pigmented Skin Lesion (ELM) in aiding diagnosis. In this work use Pigmented Skin Lesion (PSL) and analysis the images related to skin cancer. In this work also use the computational intelligence methods to examine, classify, and process the given image library. Here texture and morphological features from the given image are extracted. These results are shown in mobile data acquisition devices which in turn specify the benign (non-threatening) or malignancy (life-threatening) status of the imaged PSL. This forms the fundamental for upcoming automated classification process in term of skin lesions in skin cancer patients.

2.9   Data Mining Techniques

The data mining concepts, and their different methods are available in the literature on medical data mining [38]. In this work mainly emphasize on the data mining application on skin diseases. A classification has been offered depends on the various kinds of data mining approaches. The effectiveness of the numerous data mining procedures is highlighted. Usually, association mining is suitable for mining rules. It has been utilized particularly in cancer diagnosis. A classification is a robust approach to medical mining. This work summarized the various kinds of classification and their using process in dermatology. It is one of the most significant approaches for the diagnosis of erythematous-squamous diseases. The computer vision-based diagnosis system which discussed some clinical diagnosis approach which is being combined with the tool for detecting a different type of lesion process. In the epidermis area, finding the Melanocytes in the epidermis is a significant process and a difficult process also. Experimental evaluation based on 40 different histopathological images it comprises 341 is Melanocytes.

A novel approach for skin cancer analysis and detection from cancer effected images [41]. The image enhancement and denoising process by using Wavelet Transformation and the Asymmetry, Border irregularity, Color, Diameter (ACBD) rules are used for histogram analysis. Finally, the classification process is done by using the Fuzzy inference system. The pixel color is used for determining the final decision of 48 skin cancer type, the decision may be two stages like a malignant stage and begin the stage of skin cancer. A computer vision-based skin image Diagnosis system and Initially, in this work skin, the lesion segmentation process is done. After those vital steps are to mine the pattern and feature analysis processes to create a diagnosis of the skin cancer affected area. This work provides an idea to process the classification, detection, and segmentation of skin cancer and the skin cancer affected area utilizing a hybrid image processing approach.

The k-means algorithm, watershed method, and the difference in strength methods [27]. Initially, the image has been segmented into the different regions

by using the k-means clustering approach. From the segmented regions, the intensity value is calculated for each region, and the effective boundary and edge information is obtained by the difference strength method. Finally, the watershed algorithm is applied to each edge to analyze the broken lines in the entire image. From the region, the tumors have been segmented efficiently.

An intelligent automated approach for identifying the different sorts of skin lesions utilizing machine learning procedures [27]. Initially, local information is getting over the Local Binary Pattern (LBP) on various kinds of scales, and GLCM at different angles has been mined as a kind of texture feature. Typically, these features are robust because of scale rotation invariant property of GLCM features and invariant property of LBP. The Global information of altered color channels has been integrated through four various moments mined in six different color spaces. Thus a merged hybrid texture color and local as global features have been recommended along with SVM to categorize the non-melanoma and melanoma.

3   Proposed Method

This research work majorly focusing on the identification of skin cancers such as Malignant – Melanoma, Malignant - Basal Cell Carcinoma, Malignant - Basal Cell Carcinoma, Benign - Melanocytic Nevi, Benign - Melanocytic Nevi, Benign - Seborrheic Keratoses and Benign – Acrochordon. The detailed operation of skin cancer detection and classification approach is presented in Fig. 1.

3.1   Database Training and Testing

The database is trained from the collected images of "International Skin Imaging Collaboration (ISIC)" The dataset consisted of 1000 benign and 1000 malignant images of melanoma. All the images are trained using the BP-ANN network model with SGLD features. And random unknown test sample is applied to the system for detection and classification, respectively.

3.2   Preprocessing

The query image is obtained through the image acquisition phase, includes background data and noise. Pre-processing is mandatory to remove irrelevant information noises,labels, tape and artifacts, and the pectoral muscle from the skin image. 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 (Table 1).

Table 1. Comparison of various machine learning-based methods applied to skin cancer detection.

| Ref.	Type	Features	Method	Advantages	Challenges
[34]	Melanoma	Texture	K-NN	This method has effectively segmented the image with high accuracy	Due to texture features Asymmetry property was not fulfilled and results in inaccurate classification
[22]	Dermal cell images	Global	CNN	This method was effectively utilized to classify the dermal cells but not useful for radiologists	The Global features are majorly focused on entire image properties; thus, the background image properties affect the classification accuracy
[1]	Melanoma	Entropy controlled NCA	CNN	The multi-layer deep learning CNN architecture gives the maximum specificity	Due to neighborhood component analysis, the homogeneity and color properties will not be covered for classification
[47]	Benign, Malignant	Color	CNN	The hybrid multilayer neural network model can effectively improve the quantitative metrics	Only the color-based features are not enough to classify cancer, it also needs the asymmetry, border and texture features
[24]	Melanoma	HOG, SURF, COLOUR	Cubic SVM	The detection of cancer region extracted effectively, and multiple features are extracted	The cubic SVM is failed to classify the benign type of skin cancers and sensitivity related issues are raised
[18]	Benign, Malignant	Deep learning Features	DCNN	The multi-layer deep learning CNN architecture gives the maximum specificity	The computational complexity is much high and takes more time to extract deep learning features
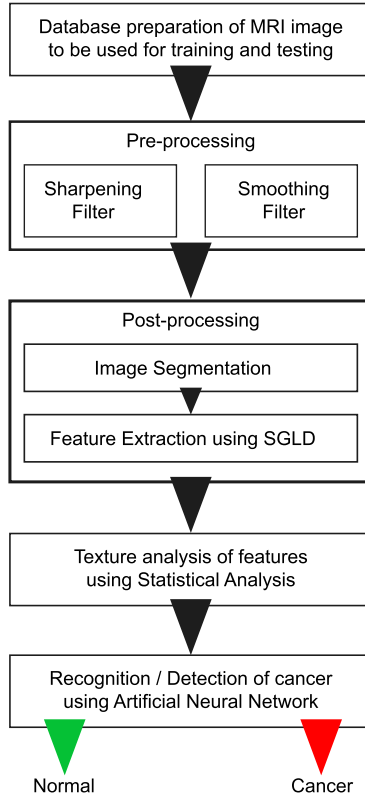
Fig. 1. Pipeline for skin cancer detection and classification.

3.3   Image Segmentation

After the preprocessing stage, segmentation of lesion was done to get the transparent portion of the affected area of skin. The Ostu's technique is utilized to the image to segment the skin lesion area based on thresholding [6]. In the Ostus algorithm, Segmentation is the initial process of this work, at the cluster centers, cost junction must be minimized which varies concerning memberships of inputs.

3.4   Feature Extraction

In this various feature can be extracted through the skin lesion to categorize various given lesions. We extracted some of the prominent features which help us in distinguishing the skin lesions, those are statistical and texture features [25]. SGLD is a statistical technique of scrutinizing textures considering the spatial connection of image pixels. The texture of mage gets characterized by SGLD functions through computations of how often pairs of pixels with explicit values and in a particular spatial connection are present in the image.

SGLD matrix can be created, and then statistical texture features are extracted from the SGLD matrix. SGLD shows how different combinations of pixel brightness values which are also known as grey levels are present in the image. It defines the probability of a particular grey level is present in the surrounding area of other grey levels. In the following formulas, let a, b be several rows and columns of matrix respectively, $S_{a,b}$ the probability value recorded for the cell (a, b), and the number of gray levels in the image be 'N'. Then several textural features (including mean, variance, standard deviation, skewness, kurtosis, contrast, correlation, dissimilarity, homogeneity, angular second movement, and energy) can be extracted from these matrices.

3.5   Texture Analysis of Features

Feature of Lesion. According to previous work on skin lesion feature extraction, computing the variance and mean of various color channels would assist in classifying the melanoma from non-melanoma images. Hence on segmenting the skin lesion image, the binary image is converted into a red, green, and blue (RGB) scale, Hue, Saturation Value (HSV), and grayscale [19]. Thus, computing the mean, variance, histograms, and non-zero bins of skin lesions in different color spaces.

Border Feature of Lesion. The border feature of the lesion is essential as melanoma has a highly irregular border as compared to the normal skin lesions. Border features can be computed by using the solidity, convex area, entropy, and convexity features.

- Solidity: It is defined as the area of the image divided by the area of its convex hull, and it is used to quantify the size and the cavities in an object boundary.
- Entropy: It is defined as the randomness of the texture of the skin lesion.
- Convex Area: It is defined as the area of the skin lesion.

3.6   Classifications of Cancer

The BP-ANN architecture has eight layers with weights. It contains the sequence of three alternating convolutional 2D layers and the MaxPooling 2D layer and three fully connected layers. The first convolutional 2D layer of the net takes in $224 \times 224 \times 3$ pixels skin lesion images and applies 96 11×11 filters at stride 4 pixels, followed by a ReLU activation layer and cross channel normalization layer. The second layer (MaxPooling) contains 3×3 filters applied at stride 2 pixels and zero paddings. Next convolutional 2D layer applies 5 256×256 pixel filters at stride 4 pixels, followed by max pooling 2D layer which contains 3×3 pixels filters applied at stride 2 pixels and zero paddings [18]. The third convolutional 2D layer of the net takes applies 384 3×3 filters at stride 1 pixel and one padding. The last dense layer of the BP-ANN contains three fully connected layers with ReLU activation and a 50% dropout to give 60 million parameters.

4   Results

4.1   Evaluation Metrics

For valuation of classification outcomes, we utilized three qualitative metrics such as specificity, accuracy and sensitivity. The accuracy can be defined as out of certain random test cases, how many outcomes give the perfect classification output. The sensitivity is defined as individual classification accuracy, how much the method is sensitive towards the malignant and benign cancers. And specificity is defined as the how much accurately the location of cancer is recognized.

– Accuracy $= \frac{TP+TN}{TP+FP+TN+FN}$
– Specificity $= \frac{TN}{TN+FP}$
– Sensitivity $= \frac{TP}{TP+FN}$

where TP conveys the amount of test cases properly recognized as malignant, FP conveys the amount of test cases improperly recognized as malignant, TN conveys the amount of test cases properly recognized as benign and FN is conveys the amount of test cases improperly recognized as benign.

4.2   Performance Comparison

In this work, three diagnosis methods are utilized such as benign skin lesion, suspicion, and melanoma. The experimental work uses 40 images comprising suspicious melanoma skin cancer. From the experimental results in this work obtain 92% classification accuracy reflects its viability. It has implemented the morphological operations for the removal of hair. The foreground is removed in the first phase using Opening operation whereas, in the second phase, the closing operation removes the background. The morphological operation has given the hair removed image that helped in further processing. Finally, Edges are detected by using Prewitt edge detection and Sobel edge detection techniques. The morphological operation gives better Peak Signal to Noise Ratio and Mean Square Error values, Prewitt edge detection is better than Sobel edge detection based on the PSNR value.

The proposed method was compared with the existing ones and as shown in Table 2, the proposed method outperformed the existing one published in the literature. The proposed method outperformed KNN [24], SVM [41], MK-SVM [18] and LSTM [38]. The superiority of the prpposed method has been clear in terms of the accuracy (97.91%), specificity (98.41%) and sensitivity (98.14%).

Also, the method was compared with techniques such as soft colour morphology [44], morphological inpainting [47], flow-guided [17] and convolutional neural network (CNN) [42]. It can be seen in Fig. 2 that the proposed method outperforms these techniques in terms of peak signal-to-noise ratio (PSNR), Structural Similarity Index (SSIM) and mean-square error (MSE).

Table 2. Comparison of performance with existing methods.

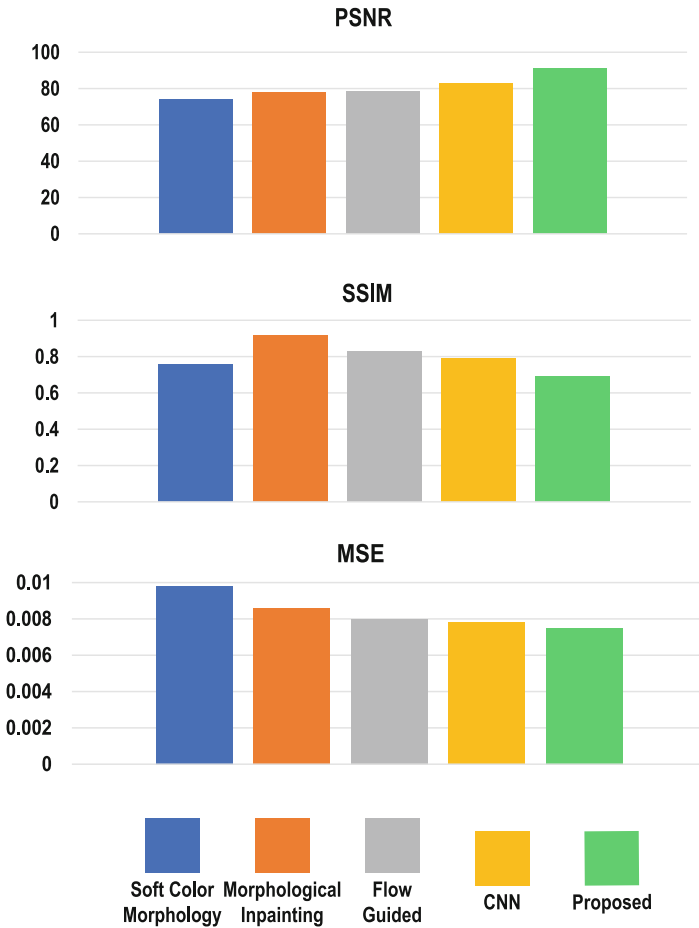| Method	Accuracy (in %)	Specificity (in %)	Sensitivity (in %)
KNN [24]	81.62	84.80	80.81
SVM [41]	75.19	72.54	78.20
MK-SVM [18]	79.90	80.08	79.72
LSTM [38]	86.02	85.02	81.02
Proposed	**97.91**	**98.41**	**98.14**

Fig. 2. Performance comparison in terms of PSNR, SSIM and MSE among popular methods and the proposed methods.

5   Conclusion

Finally, this article concludes the following challenges presented in the various literatures. By using the standard filters in preprocessing stage, they were effectively removed the noise from the images. But they are failed to remove the hair artifacts from the dermoscopy images. This results in effective segmentation. As the Melanoma is a life threatens skin cancer, it should be segmented very precisely with exact localization of borders. But conventional approaches failed to detect the cancer region accurately. The feature extraction should be done very accurately for proper classification. The state of art approaches focusing on only few categories of features but not all the types of features. The training of either deep learning or machine learning model should be done with variety of skin cancer types. But, the conventional methods failed to provide the maximum accuracy for various types of cancer. For this purpose a multi layer and error resilient back propagation based artificial network will be effectively used.

To solve this challenges, this suggests a computational methodology for the detection & classification of skin cancer from dermoscopy images using a deep learning-based approach. Here, sharpening and smoothing filters are utilized for preprocessing, which eliminates any unwanted noise elements or artifacts innovated while imaging acquisition. These filtering methods can effectively removes the hair from the skin images. Then otsu's segmentation is employed for ROI extraction and detection of cancerous cells with the accurate borders. Then the SGLD matrix method was developed for the extraction of all kind of statistical and texture features from segmented images respectively.

References

1. Akram, T., et al.: A multilevel features selection framework for skin lesion classification. Hum. Centric Comput. Inf. Sci. **10**(1), 1–26 (2020). https://doi.org/10.1186/s13673-020-00216-y
2. Al Banna, M.H., et al.: Attention-based bi-directional long-short term memory network for earthquake prediction. IEEE Access **9**, 56589–56603 (2021)
3. Al Banna, M.H., et al.: Application of artificial intelligence in predicting earthquakes: state-of-the-art and future challenges. IEEE Access **8**, 192880–192923 (2020)
4. Al Nahian, M.J., et al.: Towards artificial intelligence driven emotion aware fall monitoring framework suitable for elderly people with neurological disorder. In: Proceedings of the Brain Informatics, pp. 275–286 (2020)
5. Al Nahian, M.J., et al.: Towards an accelerometer-based elderly fall detection system using cross-disciplinary time series features. IEEE Access **9**, 39413–39431 (2021)
6. Alam, M., Tahernezhadi, M., Vege, H.K., Rajesh, P., et al.: A machine learning classification technique for predicting prostate cancer. In: 2020 IEEE International Conference on Electro Information Technology (EIT), pp. 228–232. IEEE (2020)
7. Ali, H.M., Kaiser, M.S., Mahmud, M.: Application of convolutional neural network in segmenting brain regions from MRI data. In: Proceedings of the Brain Informatics, pp. 136–146 (2019)

8. Amin, J., Sharif, A., Gul, N., Anjum, M.A., Nisar, M.W., Azam, F., Bukhari, S.A.C.: Integrated design of deep features fusion for localization and classification of skin cancer. Pattern Recognit. Lett. **131**, 63–70 (2020)

9. Aradhya, V.M., Mahmud, M., Agarwal, B., Kaiser, M.: One shot cluster based approach for the detection of covid-19 from chest x-ray images. Cogn. Comput. 1–9 (2021). https://doi.org/10.1007/s12559-020-09774-w

10. Bhapkar, H.R., Mahalle, P.N., Shinde, G.R., Mahmud, M.: Rough sets in COVID-19 to predict symptomatic cases. In: Santosh, K.C., Joshi, A. (eds.) COVID-19: Prediction, Decision-Making, and its Impacts. LNDECT, vol. 60, pp. 57–68. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-9682-7_7

11. Dascalu, A., David, E.: Skin cancer detection by deep learning and sound analysis algorithms: a prospective clinical study of an elementary dermoscope. EBioMedicine **43**, 107–113 (2019)

12. Dey, N., Rajinikanth, V., Fong, S., Kaiser, M., Mahmud, M.: Social-group-optimization assisted kapur's entropy and morphological segmentation for automated detection of covid-19 infection from computed tomography images. Cogn. Comput. **12**(5), 1011–1023 (2020)

13. Fabietti, M., Mahmud, M., et al.: Neural network-based artifact detection in local field potentials recorded from chronically implanted neural probes. In: Proceedings of the IJCNN, pp. 1–8 (2020)

14. Gaonkar, R., Singh, K., Prashanth, G., Kuppili, V.: Lesion analysis towards melanoma detection using soft computing techniques. Clin. Epidemiol. Global Health **8**(2), 501–508 (2020)

15. Han, S.S., et al.: Keratinocytic skin cancer detection on the face using region-based convolutional neural network. JAMA Dermatol. **156**(1), 29–37 (2020)

16. Hekler, A., et al.: Superior skin cancer classification by the combination of human and artificial intelligence. Eur. J. Cancer **120**, 114–121 (2019)

17. Hosny, K.M., Kassem, M.A., Foaud, M.M.: Skin cancer classification using deep learning and transfer learning. In: 2018 9th Cairo International Biomedical Engineering Conference (CIBEC), pp. 90–93. IEEE (2018)

18. Ismail, B.M., Basha, S.M., Reddy, B.E.: Improved fractal image compression using range block size. In: 2015 IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS), pp. 284–289. IEEE (2015)

19. Ismail, B.M., Reddy, T.B., Reddy, B.E.: Spiral architecture based hybrid fractal image compression. In: 2016 International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEECCOT), pp. 21–26. IEEE (2016)

20. Jesmin, S., Kaiser, M.S., Mahmud, M.: Towards artificial intelligence driven stress monitoring for mental wellbeing tracking during covid-19. In: Proceedings of the WI-IAT 2021, pp. 1–6 (2021)

21. Jesmin, S., Kaiser, M.S., Mahmud, M.: Artificial and internet of healthcare things based Alzheimer care during COVID 19. In: Mahmud, M., Vassanelli, S., Kaiser, M.S., Zhong, N. (eds.) BI 2020. LNCS (LNAI), vol. 12241, pp. 263–274. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-59277-6_24

22. Kadampur, M.A., Al Riyaee, S.: Skin cancer detection: applying a deep learning based model driven architecture in the cloud for classifying dermal cell images. Inform. Med. Unlocked **18**, 100282 (2020)

23. Kaiser, M.S., et al.: Advances in crowd analysis for urban applications through urban event detection. IEEE Trans. Intell. Transp. Syst. **19**(10), 3092–3112 (2018)

24. Khamparia, A., Singh, P.K., Rani, P., Samanta, D., Khanna, A., Bhushan, B.: An internet of health things-driven deep learning framework for detection and classification of skin cancer using transfer learning. Transactions on Emerging Telecommunications Technologies, p. e3963 (2020)
25. Lakshmi, K.N., Reddy, Y.K., Kireeti, M., Swathi, T., Ismail, M.: Design and implementation of student chat bot using aiml and lsa. Int. J. Innov. Technol. Explor. Eng. **8**(6), 1742–1746 (2019)
26. Mahmud, M., Kaiser, M.S.: Machine learning in fighting pandemics: a COVID-19 case study. In: Santosh, K., Joshi, A. (eds.) COVID-19: Prediction, Decision-Making, and its Impacts. Lecture Notes on Data Engineering and Communications Technologies, vol. 60, pp. 77–81. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-9682-7_9
27. Mahmud, M., Kaiser, M.S., Hussain, A., Vassanelli, S.: Applications of deep learning and reinforcement learning to biological data. IEEE Trans. Neural Netw. Learn. Syst. **29**(6), 2063–2079 (2018)
28. Mahmud, M., et al.: A brain-inspired trust management model to assure security in a cloud based IoT framework for neuroscience applications. Cogn. Comput. **10**(5), 864–873 (2018)
29. Marka, A., Carter, J.B., Toto, E., Hassanpour, S.: Automated detection of non-melanoma skin cancer using digital images: a systematic review. BMC Med. Imaging **19**(1), 1–12 (2019)
30. Miah, Y., Prima, C.N.E., Seema, S.J., Mahmud, M., Kaiser, M.S.: Performance comparison of machine learning techniques in identifying dementia from open access clinical datasets. In: Proceedings of the ICACIn, pp. 79–89 (2021)
31. Moqadam, S.M., Grewal, P.K., Haeri, Z., Ingledew, P.A., Kohli, K., Golnaraghi, F.: Cancer detection based on electrical impedance spectroscopy: a clinical study. J. Electr. Bioimpedance **9**(1), 17–23 (2018)
32. Munir, K., Elahi, H., Ayub, A., Frezza, F., Rizzi, A.: Cancer diagnosis using deep learning: a bibliographic review. Cancers **11**(9), 1235 (2019)
33. Nahiduzzaman, M., et al.: Machine learning based early fall detection for elderly people with neurological disorder using multimodal data fusion. In: Proceedings of the Brain Informatics, pp. 204–214 (2020)
34. Nasiri, S., Helsper, J., Jung, M., Fathi, M.: Depict melanoma deep-class: a deep convolutional neural networks approach to classify skin lesion images. BMC Bioinformatics **21**(2), 1–13 (2020)
35. Noor, M.B.T., Zenia, N.Z., et al.: Application of deep learning in detecting neurological disorders from magnetic resonance images: a survey on the detection of Alzheimer's disease, Parkinson's disease and schizophrenia. Brain informatics **7**(1), 1–21 (2020)
36. Noor, M.B.T., et al.: Detecting neurodegenerative disease from MRI: a brief review on a deep learning perspective. In: Proceedings of the Brain Informatics, pp. 115–125 (2019)
37. Orojo, O., Tepper, J., McGinnity, T., Mahmud, M.: A Multi-recurrent Network for Crude Oil Price Prediction. In: Proceedings of the 2019 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 2940–2945 (December 2019). https://doi.org/10.1109/SSCI44817.2019.9002841
38. Pacheco, A.G., Krohling, R.A.: The impact of patient clinical information on automated skin cancer detection. Computer. Biol. Med. **116**, 103545 (2020)
39. Rabby, G., et al.: TeKET: a tree-based unsupervised keyphrase extraction technique. Cogn. Comput. **12**(4), 811–833 (2020). https://doi.org/10.1007/s12559-019-09706-3

40. Rajasekhar, K., Babu, T.R.: Skin lesion classification using convolution neural networks. Indian J. Public Health Res. Dev. **10**(12), 118–123 (2019)
41. Rehman, A., Khan, M.A., Mehmood, Z., Saba, T., Sardaraz, M., Rashid, M.: Microscopic melanoma detection and classification: a framework of pixel-based fusion and multilevel features reduction. Microscopy Res. Tech. **83**(4), 410–423 (2020)
42. Roslin, S.E., et al.: Classification of melanoma from dermoscopic data using machine learning techniques. Multimedia Tools Appl. **79**(5), 3713–3728 (2020)
43. Ruiz, J., Mahmud, M., Modasshir, M., Kaiser, M.S., et al.: 3d densenet ensemble in 4-way classification of Alzheimer's disease. In: Proceedings of the Brain Informatics, pp. 85–96 (2020)
44. Shahane, R., Ismail, M., Prabhu, C.: A survey on deep learning techniques for prognosis and diagnosis of cancer from microarray gene expression data. J. Comput. Theor. Nanoscience **16**(12), 5078–5088 (2019)
45. Singh, A.K., Kumar, A., Mahmud, M., Kaiser, M.S., Kishore, A.: Covid-19 infection detection from chest x-ray images using hybrid social group optimization and support vector classifier. Cogn. Comput. 1–13 (2021). https://doi.org/10.1007/s12559-021-09848-3
46. Watkins, J., Fabietti, M., Mahmud, M.: Sense: a student performance quantifier using sentiment analysis. In: Proceedings of the IJCNN, pp. 1–6 (2020)
47. Wibowo, A., Hartanto, C.A., Wirawan, P.W.: Android skin cancer detection and classification based on mobilenet v2 model. Int. J. Adv. Intell. Inform. **6**(2), 135–148 (2020)
48. Yahaya, S.W., Lotfi, A., Mahmud, M.: A consensus novelty detection ensembleapproach for anomaly detection in activities of daily living. Appl. SoftComput. **83**, 105613 (2019)
49. Yahaya, S.W., Lotfi, A., Mahmud, M.: Towards a data-driven adaptive anomaly detection system for human activity. Pattern Recognit. Lett. **145**, 200–207 (2021)