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Comperative assessment of taylor water cycle optimization (TWCO) -based deep residual network (DRN) for skin cancer detection using deep learning

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***Abstract*---**This paper devises a hybrid optimization driven deep technique for automated detection of skin cancer. Here, the pre-trained deep learning model is utilized for the skin cancer detection. The pre-processing of skin images is performed that helped to reduce the ill impacts and several artifacts such as hair that may be contained in the dermoscopy images. In addition, the DeepJoint model is used to perform segmentation in order to attain improved outcomes. The data augmentation helped to make the image suitable for improved processing helps to quantify the images for effective classification. The skin cancer detection is done with Deep Residual Network (DRN), which is trained using newly devised technique, namely Taylor Water Cycle Optimization (TWCO) algorithm. The proposed TWCO-based DRN outperformed with highest testing accuracy of 92.3%, True positive rate (TPR) of 93.5% and True negative rate (TNR) of 90.5%.

***Keywords*---**deep residual network, skin cancer detection, deep joint segmentation, roi extraction, data augmentation.

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Introduction

The skin cancer detection is done with Deep Residual Network (DRN), which is trained using newly devised technique, namely Taylor Water Cycle Optimization (TWCO) algorithm. The proposed TWCO-based DRN outperformed with highest testing accuracy of 92.3%, True positive rate (TPR) of 93.5% and True negative rate (TNR) of 90.5%. The disease in skin can be cancerous, infectious, or inflammatory and it may influence people of all ages particularly the eldest and younger kids. There exist serious issues of skin disease like death and mutilation in daily tasks. In addition, it also contains a real risk of mental sickness which can lead to depression, seclusion and suicide [15] [2]. The Melanoma is a major type of skin disease that influences the surfaces of skin cells termed as melanocytes. It comprises cells which causes skin to turn black. Melanoma can be determined in dark colour at some phase as it can be in purple, red or white in color. This type of cancer is troubling as it poses the propensity to cause metastasis which represents the capability to spread. The Melanoma can be discovered anywhere in the body of human, but it is mostly devised in legs of human [16]. It poses the potential to spread quickly and made it hazardous and incurable [1]. The cancer in skin is most general malignancy in several white-skinned peoples and the occurrence of non-melanoma and melanoma skin cancer becomes rising that may result to elevated costs. Earlier diagnosis of melanoma tends to enhance the outcomes of patients and detection of skin cancer can be enhanced with several techniques like screening patients with symptoms of skin considering skin inspections [18] [19]. Earlier discovery of skin cancer melanoma is complex and it needs more focus [17].

Considering each individual, the aspects of risks in skin cancer can be minimized by discovering it timely or prior time in earlier phase. In general, the major reduction in the rate of mortality can be attained by discovering the skin cancer in earlier phases. Thus, the discovery and classification of disease in prior phases are imperative. The Asymmetry, Border, Colour, and Diameter (ABCD) rule is utilized by clinicians for discovering the melanoma [20] [1]. In [21] [4], the deep neural network (DNN) is used for classifying the skin cancer amongst the humans. The analysis is done with various images considering three way and nine way classification techniques. They trained DNN with 129,450 images. This method is able to identify cancer using images. In [22] [4], an enhanced Particle Swarm Optimization is devised for discovering skin cancer. The outcomes of this technique are compared to other optimization techniques. This technique is capable to generate best outcomes for selecting features and assist to attain best solution for detecting skin cancer. In [12] [4], a genetic technique is devised for detecting skin cancer. To analyze the skin soreness and to categorize it into benign and melanoma, various methods like artificial neural networks (ANNs), genetic algorithms, Convolutional Neural Network (CNN), support vector machines (SVMs), and ABCD rule are devised in [23]. The most effective way to attain skin cancer detection is computer vision and establishes the service as binary image classification that can be either malignant or benign.

The diseases in skin have been an issue in medical treatment because of visual similarities. Even though, melanoma is known skin cancer, there exist other pathologies that may lead to high mortality rate. The deficiency of huge databases is the major complexity to design an automated system. The goal is to devise a technique for detecting the skin cancer using the set of input images. The input image is attained from the dataset and it undergoes RoI extraction to extract interesting regions. The segmentation is done with the DeepJoint model [25] to mine the segments. The data augmentation is done to make the data suitable for enhanced processing. The classification of skin cancer is done using DRN [24]. The proposed TWCO is employed for training DRN to detect the skin cancer. The developed TWCO approach is obtained by combining the WCA [26] and Taylor series [27].

Proposed System

The input to DRN is segments, which are denoted by . DRN [24] is adapted for making effective decision wherein the detection of skin cancer is performed. The DRN helps to enhance vanishing-gradient issue and helps to strengthen the features propagation. It helps to reprocess the features and minimize the number of attributes. It is association and produces precise outcomes. The DRN training is performed with proposed TWCO. Here, the WCA [26] is inspired through the nature and developed with the observation of water cycle and river and streams flowing through sea in real-time. The WCA comprises capability to address various optimization and engineering problems. Furthermore, the WCA is effective in providing quality solutions and comprises improved computational efficiency. The method is adapted for addressing real world problems with acceptable solution accuracy. It is effective in managing several combinatorial optimization issues, and provides best solution with less computational efforts. Taylor series [27] defines the function of complex parameters with various terms. The incorporation of both Taylor series with WCA attains effective efficiency by addressing optimization issues.

Results and Discussion

The efficiency of proposed TWCO-based DRN is computed by assessing the techniques with different measures, like TPR, TNR, and accuracy.

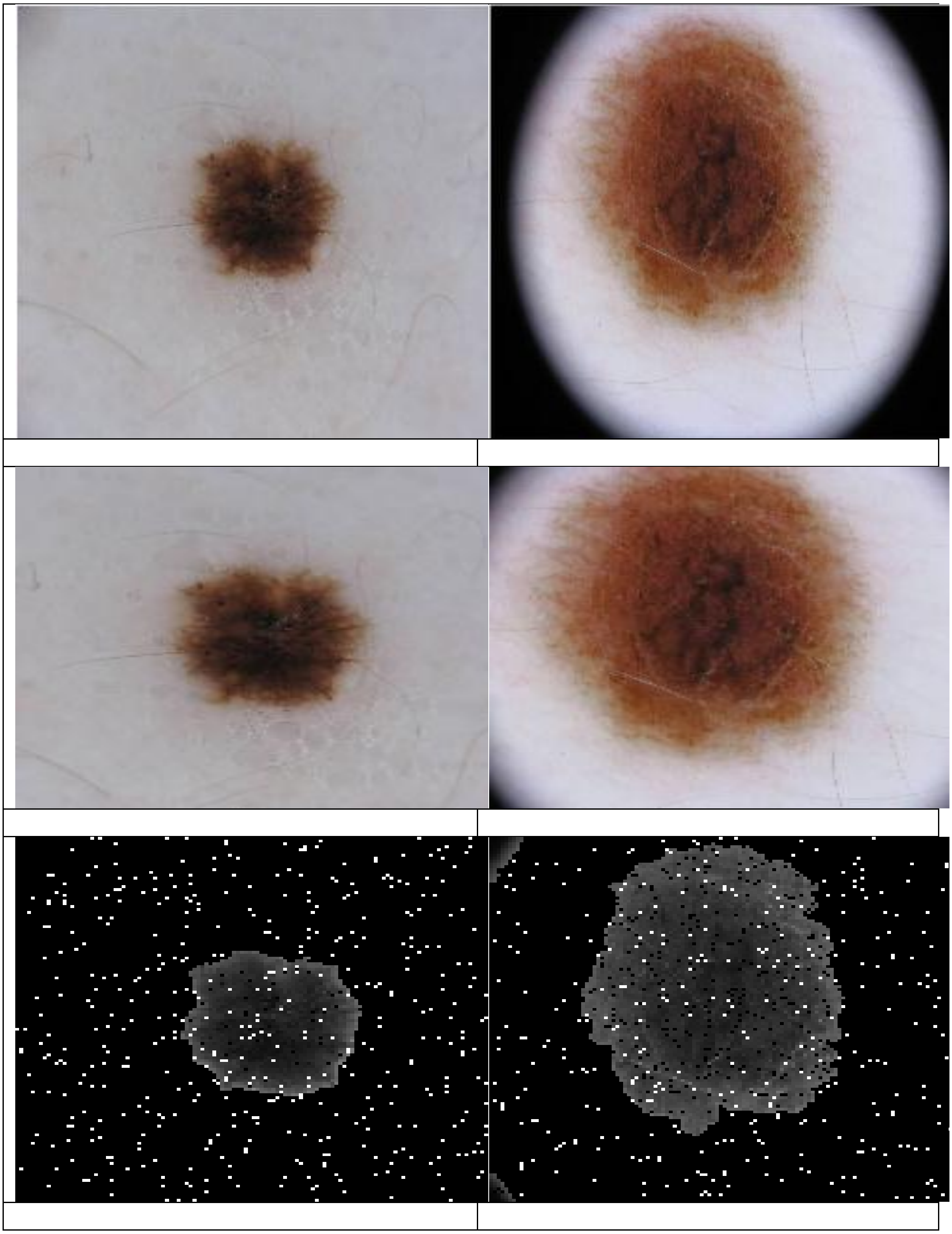
Experimental setup

The implementation of developed technique is performed in PYTHON tool having windows 10 OS, 4GB RAM, and Intel processor.

Dataset description

The analysis is done using ISIC 2019 dataset [28]. The dataset contains dermatoscopic images of most frequent skin lesions like Squamous Cell Carcinoma, Actinic Keratosis, Seborrheic Keratosis, Basal Cell Carcinoma, Nevi, Melanoma, Solar Lentigo, Dermatofibroma, and Vascular Lesions. The images are adapted through the Department of Dermatology.

Experimental results



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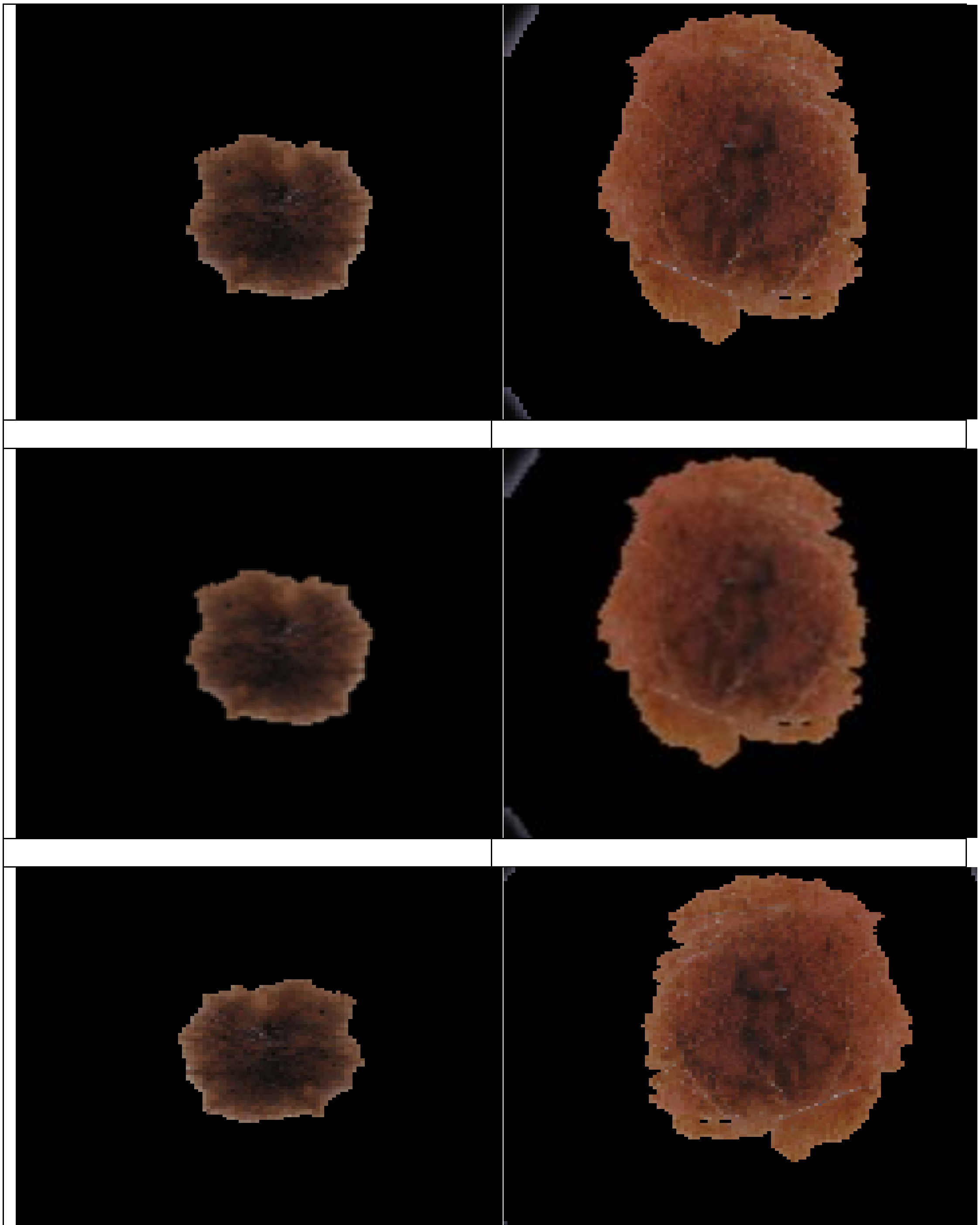


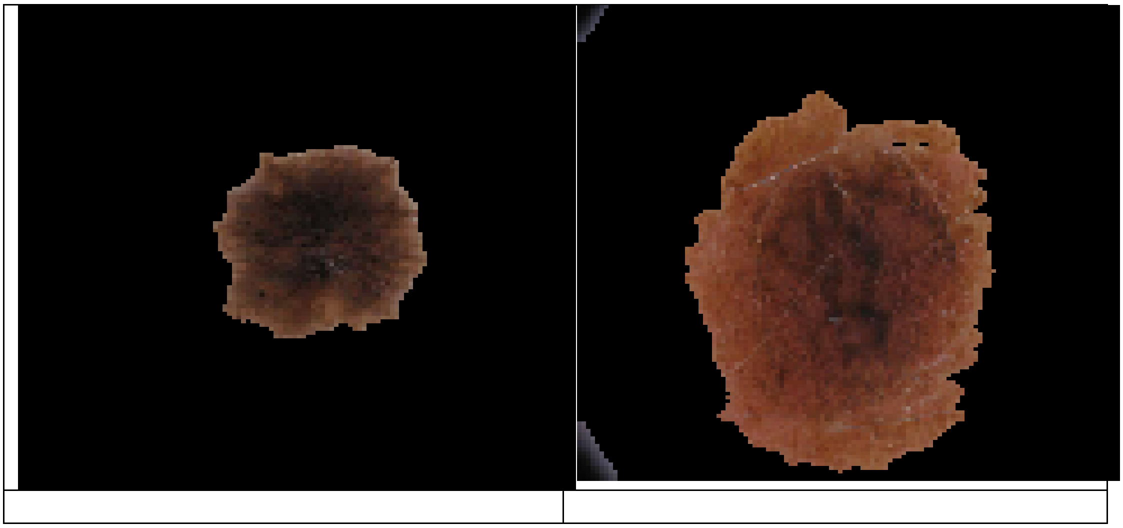


Figure 3. Experimental outcomes of proposed TWCO-based DRN using a) Input image b) RoI extraction c) Added Noise image d) Segmented image e) Zoomed image f) Flipped image lower g) Flipped image upwards

Figure 3 displays the experimental outcomes of proposed TWCO-based DRN using input images. The input images accumulated for detecting skin cancer is revealed in figure 3a). The RoI extraction is revealed in figure 3b). The Added Noise image is displayed in figure 3c). The segmented image is revealed in figure 3d). The zoomed image is exposed in figure 3e). The flipped image lower is displayed in figure 3f). The flipped image upwards is exposed in figure 3g).

Evaluation measures

The efficiency of developed model is analyzed by adapting measures, like accuracy, TPR, and TNR.

Accuracy

It is defined as a measure of data which is precisely preserved and is expressed as,

$$M = \frac{P+Q}{P+Q+H+F} \tag{39}$$

Where, P signifies true positive, Q symbolize true negative, F denote true false positive, and H is false negative.

TPR

TPR: It is described as a ratio of count of true positives with respect to total count of positives.

$$TPR = \frac{P}{P+H} \tag{40}$$

Where, P refers true positives, H is the false negatives.

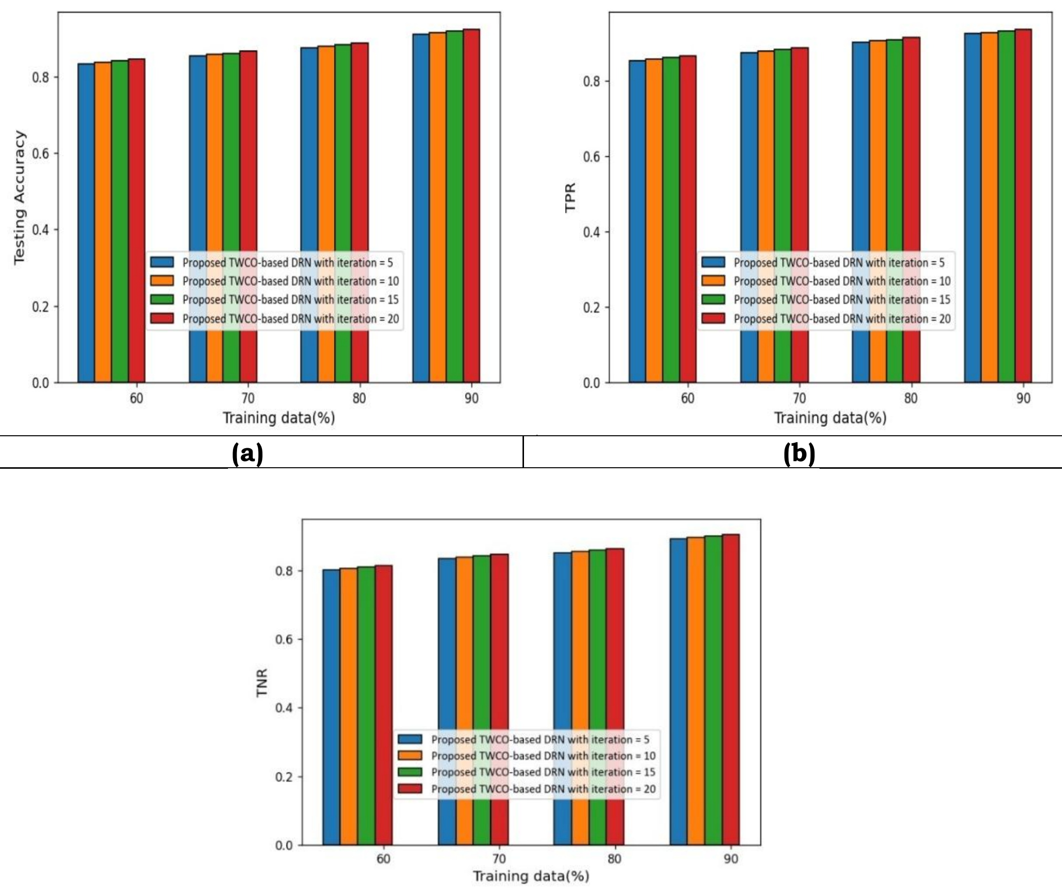
TNR

It refers the ratio of negatives which are correctly detected.

$$TNR = \frac{Q}{Q+F} \tag{41}$$

Where, Q is true negative and F signifies false positive.

Performance assessment



(a) **(b)**

(c)

Figure 3. Assessment of proposed TWCO-based DRN using a) Testing accuracy b) TNR c) TPR

Figure 3 displays the assessment of proposed TWCO-based DRN by altering training data. The assessment with testing accuracy is displayed in figure 3a). For 60% training data, the testing accuracy generated by proposed TWCO-based DRN with iteration 5, 10, 15 and 20 are 0.833, 0.837, 0.841, and 0.846. Similarly, for 90% training data, the testing accuracy generated by proposed TWCO-based DRN with iteration 5, 10, 15 and 20 are 0.911, 0.916, 0.919, and 0.923. The assessment with sensitivity displayed in figure 3b). For 60% training data, the sensitivity generated by proposed TWCO-based DRN with iteration 5, 10, 15 and 20 are 0.852, 0.857, 0.860, and 0.865. Similarly, for 90% training data, the sensitivity generated by proposed TWCO-based DRN with iteration 5, 10, 15 and 20 are 0.923, 0.927, 0.931, and 0.935. The assessment with specificity is displayed in figure 3c). For 60% training data, the specificity generated by proposed TWCO-based DRN with iteration 5, 10, 15 and 20 are 0.802, 0.806, 0.810, and 0.814. Similarly, for 90% training data, the specificity generated by proposed TWCO-based DRN with iteration 5, 10, 15 and 20 are 0.892, 0.897, 0.901, and 0.905.

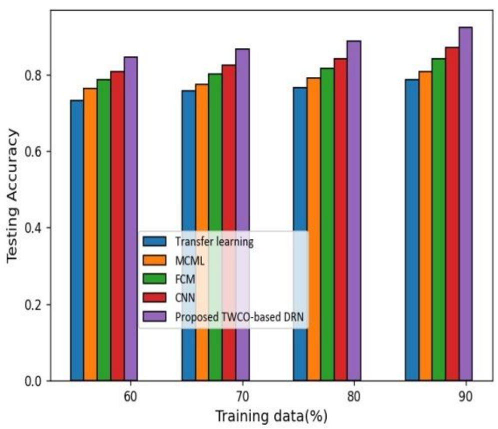
Comparative techniques

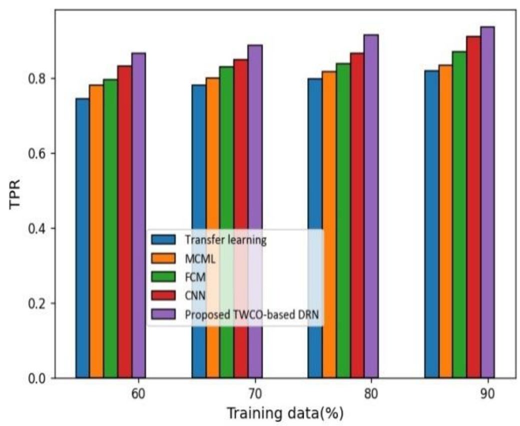
The techniques considered for the assessment includes Transfer learning [1], MCML [2], FCM [4], CNN [5] and proposed TWCO-based DRN.

Comparative assessment

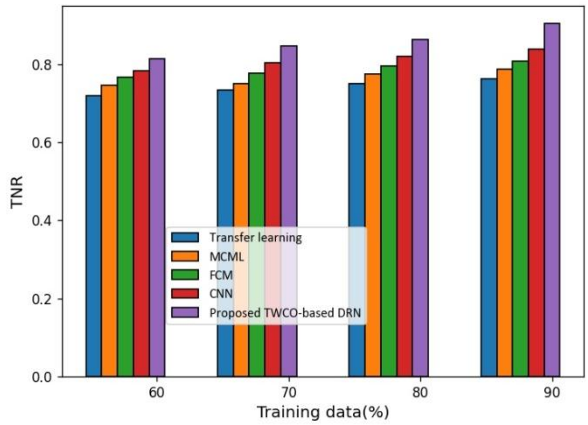
The assessment of developed technique is performed by adapting certain measures like accuracy, TPR and TNR. Here, the assessment is done by changing training data and K-fold.

Assessment without training data





(a)	(b)

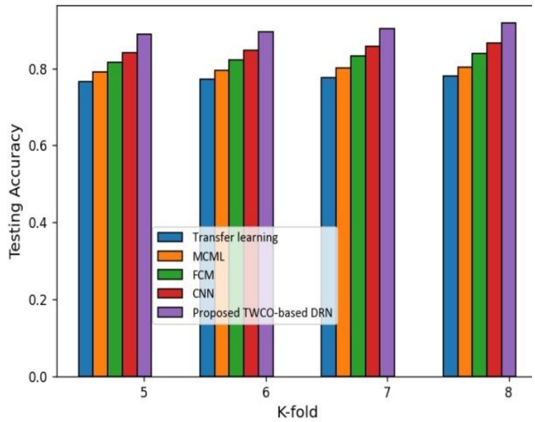


(c)

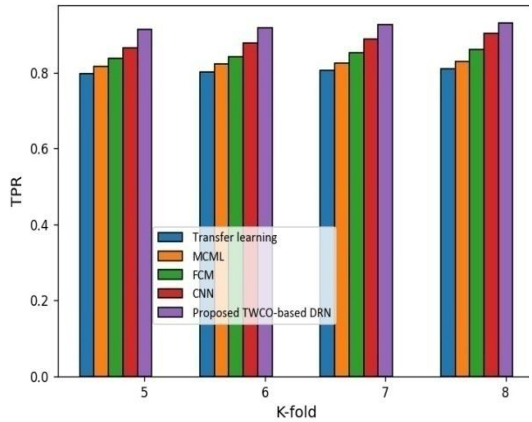
Figure 4. Assessment of techniques with training data using a) Testing accuracy b) TNR c) TPR

The assessment of techniques by varying training data is shown in Figure 4. The assessment considering testing accuracy is exposed in figure 4a). Considering 60% training data, the highest testing accuracy of 0.846 is produced by proposed TWCO-based DRN while the testing accuracy of Transfer learning, MCML, FCM, CNN are 0.733, 0.765, 0.787, 0.807. Similarly, for 90% training data, the highest testing accuracy of 0.923 is generated by proposed TWCO-based DRN while the testing accuracy of Transfer learning, MCML, FCM, CNN are 0.787, 0.808, 0.842, 0.871. The efficiency of Transfer learning, MCML, FCM, CNN in contrast to TWCO-based DRN using testing accuracy are 14.734%, 12.459%, 8.775%, 5.633%. The assessment with TNR displayed in figure 4b). For 60% training data, the highest TNR of 0.865 is generated by proposed TWCO-based DRN while the TNR of Transfer learning, MCML, FCM, CNN is 0.744, 0.780, 0.794, and 0.830. Similarly, for 90% training data, the highest TNR of 0.935 is generated by proposed TWCO-based DRN while the TNR of Transfer learning, MCML, FCM, CNN is 0.818, 0.832, 0.870, and 0.909. The efficiency of Transfer learning, MCML, FCM, CNN in contrast to TWCO-based DRN using TNR are 12.513%, 11.016%, 6.951%, 2.780%. The assessment with TPR is displayed in figure 4c). For 60% training data, the highest TPR of 0.814 is generated by proposed TWCO-based DRN while the TPR of Transfer learning, MCML, FCM, CNN is 0.720, 0.746, 0.767, and 0.784. Similarly, for 90% training data, the highest TPR of 0.905 is generated by proposed TWCO-based DRN while the TPR of Transfer learning, MCML, FCM, CNN is 0.762, 0.786, 0.808, and 0.838. The efficiency of Transfer learning, MCML, FCM, CNN in contrast to TWCO-based DRN using TPR are 15.801%, 13.149%, 10.718%, 7.403%.

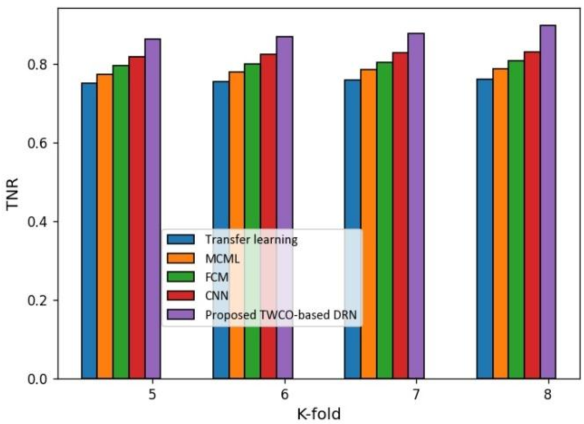
Assessment without K-fold



(a)



(b)



(c)

Figure 5. Assessment of techniques with K-fold using a)Testing accuracy b) TNR c) TPR

The assessment of proposed Taylor-WCA-based DRN by altering k-fold is depicted in Figure 5. The assessment considering testing accuracy is exposed in figure 5a). Considering K-fold=5, the testing accuracy generated by Transfer learning, MCML, FCM, CNN are 0.765, 0.791, 0.816, 0.841, while that of proposed TWCO-based DRN is 0.888. Similarly, for K-fold=8, the testing accuracy generated by Transfer learning, MCML, FCM, CNN are 0.781, 0.804, 0.839, 0.866, while that of proposed TWCO-based DRN is 0.918. The efficiency of Transfer learning, MCML, FCM, CNN in contrast to TWCO-based DRN using testing accuracy are 14.923%, 12.418%, 8.605%, 5.664%. The assessment with TNR displayed in figure 5b). For K-fold=5, the TNR generated by Transfer learning, MCML, FCM, CNN are 0.797, 0.816, 0.836, 0.865, while that of proposed TWCO-based DRN is 0.913. Similarly, for K-fold=8, the TNR generated by Transfer learning, MCML, FCM, CNN are

0.810, 0.829, 0.861, 0.902, while that of proposed TWCO-based DRN is 0.930. The efficiency of Transfer learning, MCML, FCM, CNN in contrast to TWCO-based DRN using TNR are 12.903%, 10.860%, 7.419%, 3.010%. The assessment with TPR is displayed in figure 5c). For K-fold=5, the TPR generated by Transfer learning, MCML, FCM, CNN are 0.751, 0.774, 0.796, 0.819, while that of proposed TWCO-based DRN is 0.863. Similarly, for K-fold=8, the TPR generated by Transfer learning, MCML, FCM, CNN are 0.762, 0.789, 0.809, 0.831, while that of proposed TWCO-based DRN is 0.898. The efficiency of Transfer learning, MCML, FCM, CNN in contrast to TWCO-based DRN using TPR are 15.144%, 12.138%, 9.910%, 7.461%.

Comparative discussion

Table 2 displays the comparative assessment using techniques considering training data and K-fold. Using training data, the highest testing accuracy of 0.923 is measured by proposed TWCO-based DRN while the testing accuracy of Transfer learning, MCML, FCM, CNN are 0.787, 0.808, 0.842, and 0.871. The highest testing accuracy occurs due to DRN which helps in making the skin cancer detection more accurate. The highest TPR of 0.935 is measured by proposed TWCO-based DRN while the TPR of Transfer learning, MCML, FCM, CNN are 0.818, 0.832, 0.870, and 0.909. The proposed model is good in predicting the true positives correctly and thus the TPR tends to be very high. The highest TNR of 0.905 is measured by proposed TWCO-based DRN while the TPR of Transfer learning, MCML, FCM, CNN is 0.762, 0.786, 0.808, and 0.838. The high TNR reveals that developed technique is effectual in predicting true negatives. Using K-fold, the highest testing accuracy of 0.918, TPR of 0.930 and TNR of 0.898 is generated by proposed TWCO-based DRN.

Table 2
Comparative assessment

Variation	Metrics	Transfer learning	MCML	FCM	CNN	Proposed TWCO-based DRN
Training data	Testing accuracy	0.787	0.808	0.842	0.871	0.923
	TPR	0.818	0.832	0.870	0.909	0.935
	TNR	0.762	0.786	0.808	0.838	0.905
K-fold	Testing accuracy	0.781	0.804	0.839	0.866	0.918
	TPR	0.810	0.829	0.861	0.902	0.930
	TNR	0.762	0.789	0.809	0.831	0.898

Conclusion

Here, the segmentation is done using Deep Joint model whose goal is to alter the image representation that is into smaller segments which is easy to examine. The data augmentation is adapted for making the image suitable for attaining enhanced processing. The proposed TWCO-based DRN is offered for detecting the skin disease. Here, the weight update process of DRN is done by optimally tuning the DRN weights, which is eventually done using proposed TWCO and is devised by blending Taylor series and WCA. Hence, this method effectually discovered the skin diseases in its earlier phases. The future work involves the consideration of other advanced datasets for checking the feasibility of the designed model. The proposed TWCO-based DRN offered good presentation with highest testing accuracy of 92.3%, TPR of 93.5% and TNR of 90.5%.

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