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Modeling of Crow Search Algorithm with Deep Learning for Skin Cancer Diagnosis on Dermoscopic Images

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Abstract

Initial and correct analysis of skin cancer is vital in decreasing mortality and morbidity connected with this dominant disease. Dermoscopic images provide a magnified outlook of skin injuries and vital information for dermatologists and researchers. This research mainly concentrated on the growth of an innovative framework for the analysis of skin cancer employing dermatoscopic images and a state-of-the-art approach in image analysis and machine learning (ML). This study develops Crow Search Algorithm with Deep Learning for Skin Cancer Diagnoses on Dermoscopy Images (CSADL-SCDDI) model. We use Bilateral filter (BF) for preprocessing to improve quality of dermatoscopic images. For feature extraction, we influence SqueezeNet technique. This model is a lightweight DL design which is well-known for its efficacy in removing significant features from images. These removed features capture serious data needed for precise skin cancer detection. The classification step is executed by utilizing Recurrent Neural Networks (RNNs). RNNs are effective and suitable for consecutive data analysis and grab time-based dependencies within feature representations which is perfect for differentiating between benign and malignant skin cancer. To improve the performance of the detection method, we use CSA for parameter tuning. CSA is a nature-inspired optimization model that enhances the hyper-parameter of RNN as well as exploits diagnostic precision method. The developed framework is estimated on a huge dataset of dermatoscopic images, representing its efficiency in skin cancer analysis. This complete technique provides excessive ability for the improvement of vigorous and precise skin cancer analytic systems with potential applications in medical settings in order to help dermatologists make decisions on time and more informative.

Keywords: Skin cancer; Deep learning; Crow search algorithm; Bilateral filter; Recurrent neural network

1. Introduction

Generally, skin cancers are mainly affected by the development of irregular cells that are reliant on their intensity as well as nature, which spread to dissimilar parts of the body [1]. Meanwhile, the skin is most visible tissue to eco-friendly toxins which is so weak. Skin cancer is most common when compared to all cancers. Nearly 46,000 novel skin cancer cases are stated every year in the state of UK [2]. This cancer is separated into 3 forms namely Squamous cell skin cancer (SCC), Basal cell skin cancer (BCC), and Melanoma. The initial dual forms of skin cancers are categorized as non-melanoma which is hardly prime to death [3]. Melanoma is a deadly kind of skin cancer. One of the key causes of this cancer is UV emission directly from the sun. The fair-skinned type has a higher danger of skin cancer when compared to dark skinned, which might be owing to superb defense delivered by the stain in layers that are openly visible [4].

Melanoma is a cancer that initiates in melanin making cells and originates mainly on the skin, eyes, meninges as well as nerve centres [5]. If diagnosed at an initial stage, it is further probable to be healed, despite the maximum amount of growing occurrence amid all kinds of skin cancers. The on-time and early recognize of skin cancer will decrease the death level by 90 percentage [6]. Patients in phase I have 10 years complete living chance from 94 to 98 percentage, whereas stage IV have predictable 10 years total living of only 10 to 15 percentage. Melanoma is more collective in a few people when evaluated with others. Identifying these clusters can aid in preventing these highly challenging risk conditions [7]. The identification procedure of a disease can become slow as well as time-consuming for a dermatologist. So, the main goal would be the development of a rapid, well-organized as well as exact technique for the analysis of malignant lesions in its primary phase [8]. Therefore, a non-invasive computer-aided diagnosis (CAD) model should be measured for regular practice that releases the patients from the difficulty of invasive pathology as well as raises the exactness and rapidity of diagnosis [9]. Development in Machine Learning and segmentation models have upgraded CAD systems as well as sorting of deadly skin cancerous diseases over the past years [10]. CAD systems have been removed from desktops and workstations to smartphones and allow pathologist to identify malignant lesion which is not noticeable to human eyes.

Zhou et al. [11] proposed an effective and novel technique namely Multi-Site Cross-Organ Calibration based-DL (MuSClD) which uses WSIs of *off-target* tissues for normalization formed at a related region as *on-target* tissues. The author defined that by using an off-target tissue from the test area for adjusting trained data, the area transfer among trained as well as verified data can be improved. Bassel et al. [12] presented a technique based upon the loading of a classification algorithm with three folds for categorizing benign as well as melanoma skin cancers. The model is tested in three stages through RF, KNN, NN, LR, SVM, and DL techniques with 1000 skin imageries to detect benign and melanoma. The main feature removal is executed by utilizing Resnet50, VGG16, and Xception models. In [13], the author designed dual unique hybrid CNN techniques by SVM technique at the output layer to organize dermoscopy imageries for melanoma as well as benign cancers. This feature removal through the CNN model is combined and then delivered to the SVM method for grouping. The class labels achieved from expert dermatologists have been employed as the circumstances for evaluating the competencies of advanced models.

This study develops Crow Search Algorithm with Deep Learning for Skin Cancer Diagnoses on Dermoscopy Images (CSADL-SCDDI) model. We use Bilateral filter (BF) for preprocessing to improve quality of dermatoscopic images. For feature extraction, we influence SqueezeNet technique. The classification step is executed by utilizing Recurrent Neural Networks (RNNs). RNNs are effective and suitable for consecutive data analysis and grab time-based dependencies within feature representations which is perfect for differentiating between benign and malignant skin cancer. To improve the performance of the detection method, we use CSA for parameter tuning. CSA is a nature-inspired optimization model that enhances the hyper-parameter of RNN as well as exploits diagnostic precision method. The developed framework is estimated on a huge dataset of dermatoscopic images, representing its efficiency in skin cancer analysis.

2. The proposed model

This study suggests a complete framework for skin cancer analysis depending on dermatoscopic images. This technique combines advanced models in feature extraction, pre-processing, parameter optimization and classification. Fig. 1 depicts the entire procedure of CSADL-SCDDI algorithm.

2.1. Preprocessing

We use BF for pre-processing to improve quality of dermatoscopic images. The BF assists as an important pre-processing tool. It plays a vital part role in enhancing the quality as well as efficacy of these images by decreasing noise and improving key structural features. The BF is respected in holding edge and fine texture details while efficiently justifying unwanted sound. This results in cleaner and more diagnostically informative images. This step is essential to improve the accuracy of ensuing image analysis and detection thus simplifying initial and trustworthy recognition of skin cancer. It can expand patient results and the effectiveness of medical involvement in the dermatology field.

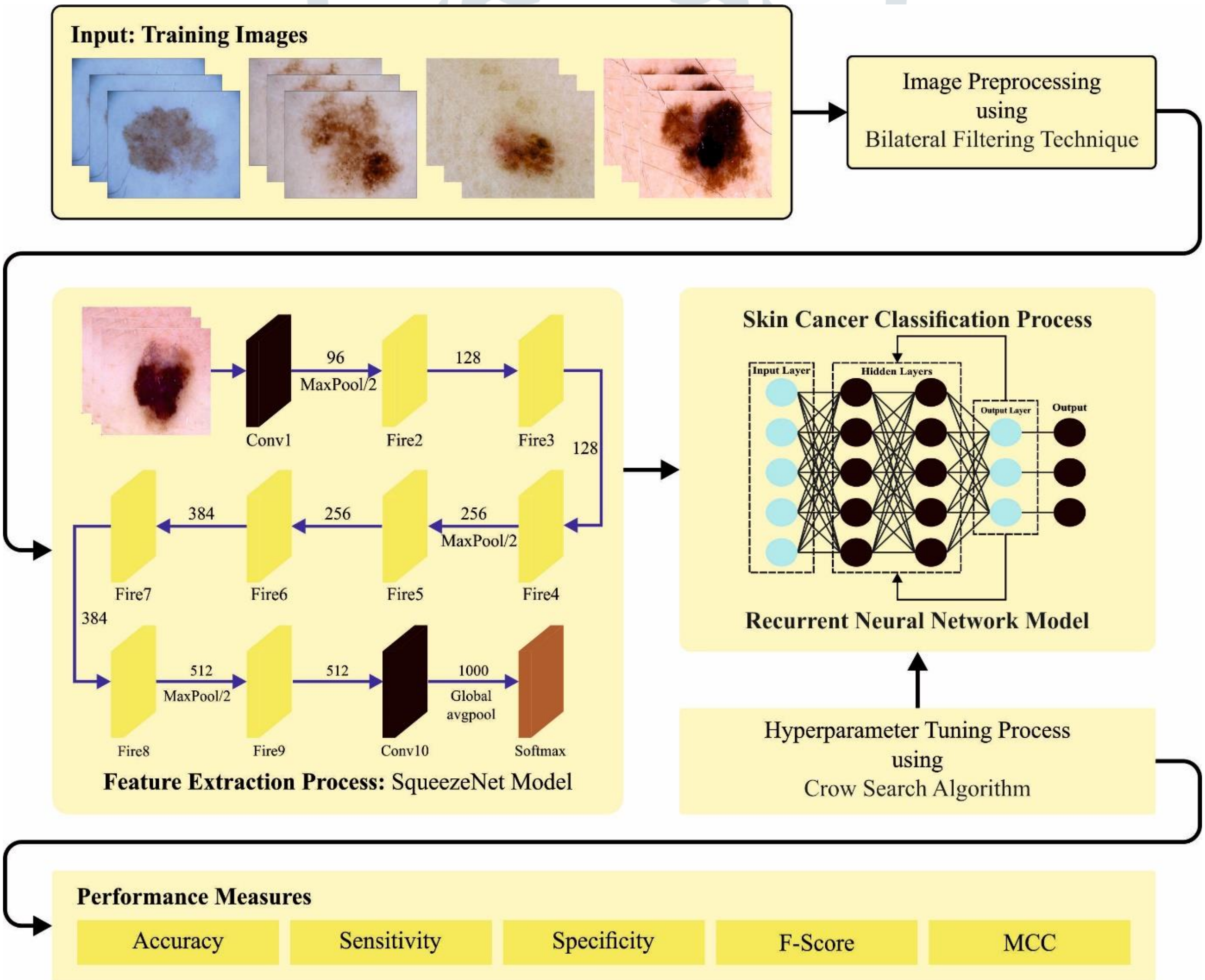

Fig. 1. Overall procedure of CSADL-SCDDI approach

2.2. Feature extraction using SqueezeNet model

For feature extraction, we use SqueezeNet method. Feature extraction through the SqueezeNet technique is more powerful in the area of computer vision as well as image analysis [15]. SqueezeNet's distinct framework is specially designed to offer an effectual method to capture dangerous features from images. By squeezing down the amount of limits without cooperating performance, SqueezeNet excels in removing fine-grained features that are helpful in distinctive designs and patterns within images. In skin cancer analysis or other image-based detection tasks, this feature extraction method simplifies formation of revealing and compressed symbols that permit machine learning (ML) technique to generate more accurate differences. This contributes to improved diagnostic accuracy and healthcare outcomes.

2.3. Classification using RNN

The classification phase is carried out using an RNN technique. Neurons in RNNs can convey data to one another when compared to other customary neural networks [16]. So RNN is measured greater. RNN functions according to time sequence so it is a highly beneficial technique for executing time series tasks.

where x is input; y is prediction outcome; S is the hidden state then $U,$ V, and W are inputhidden, hiddenoutput, and hiddenhidden weight matrices correspondingly. Hence, RNN is a time series method; the performance and state of the system are tested in time. The input of current χ_i of the system and preceding time-state S_{t-1} define neuron state S at time t is considered as below:

$$S_t = F(Ux_{t-1} + WS_{t-1} + b_h) \quad (1)$$

where F is the beginning function and b_h is a bias period. The neuron state S_t employed as output at time t and input of network state at subsequent time $t+1$ at similar time.

Since S_t cannot be output as a result in a straight way, it desires to be increased by constant V and then further offset. This stage is denoted via the subsequent measured formula:

$$y_t = Act\left(VS_t + b_y\right) \quad (2)$$

where Act is the activation function and then b_y is a bias term.

2.4. Parameter tuning using CSA method

To fine-tune the performance of the classification model, we employ the CSA for parameter tuning. Crow search (CS) is a new population swarm intelligent technique, and its search agent was modelled as a crow [17]. It can able to search, steal, conceal, and recognize various kinds of food. Due to this intelligence, the crows have characteristics represented as awareness probability (AP). It explores the crow from all angles and works towards searching for the optimum solution. It achieves the optimum solution while bringing the stabilization of exploitation and exploration. The search agent positioned in the d-direction is evaluated as follows:

$$\left[X^{a,iter} = X_1^{a,iter}, X_2^{a,iter}, \ldots X_d^{a,iter}\right], \quad (3)$$

In Eq. (3), $iter = 1,2,\ldots,iter_{\max}$ and $a = 1,2,\ldots,flock\ size\ (n)$. Two possibilities are available to track and store the crow location in iteration.

Possibility 1: crow-p approaches the walloping location and is transported by crow-q unaware of the presence of crow-q behind them and is shown below:

$$X^{p,iter+1} = X^{p,iter} + r \times Flight\ Length^{p,iter} \times \left(m^{q,iter} - X^{q,iter}\right) r \geq AP^{q,iter}. \quad (4)$$

Possibility 2: predicting that crow-q is close behind, it turned off and is now positioned at a random place:

$$X^{p,iter+1} = random\ position, \quad (5)$$

Here memory (m), flight length is 0.2, AP is 0.1, and random $(0 \leq r \leq 1)$. At small and large values of flight length, the optimal solution is globally and locally found. When performing iteration, reducing the values of AP produces a diversification (better solution), and increasing the values of AP leads to intensification (better outcome). During iteration, the property of intensification and diversification was determined using AP. With the decrease of AP, it provides the optimum solution, and intensification is better at the smallness of AP. Here, the parameters tuned are maximum generation $\left(\max_{gen} = 500\right)$, $lock\ size\ (n = 50)$, and population size $(Pop_{size} = 50)$.

3. Result analysis

The experimental analysis of the CSADL-SCDDI system is assessed on test database. The dataset contains 2000 samples with three classes as described in Table 1.

Table 1 Details on database

Class	Label	No. of Samples
Melanoma	Class-1	374
Seborrheic Keratosis	Class-2	254
Nevus	Class-3	1372
Total Number of Samples		**2000**

Fig. 2 exhibits the classifier analysis of the CSADL-SCDDI system in test database. Figs. 2a-2b shows the confusion matrices offered by the CSADL-SCDDI method with 70:30 of TR phase/TS phase. The figure indicated that the CSADL-SCDDI model has properly identified and categorized with 3 classes. Additionally, Fig. 2c exhibits the PR analysis of the CSADL-SCDDI approach. The figure pointed out that the CSADL-SCDDI methodology achieves excellent PR performance with each class. Also, Fig. 2d represents the ROC analysis of the CSADL-SCDDI model. The figure revealed that the CSADL-SCDDI algorithm accelerates proficient outcomes with greater ROC values in different classes.

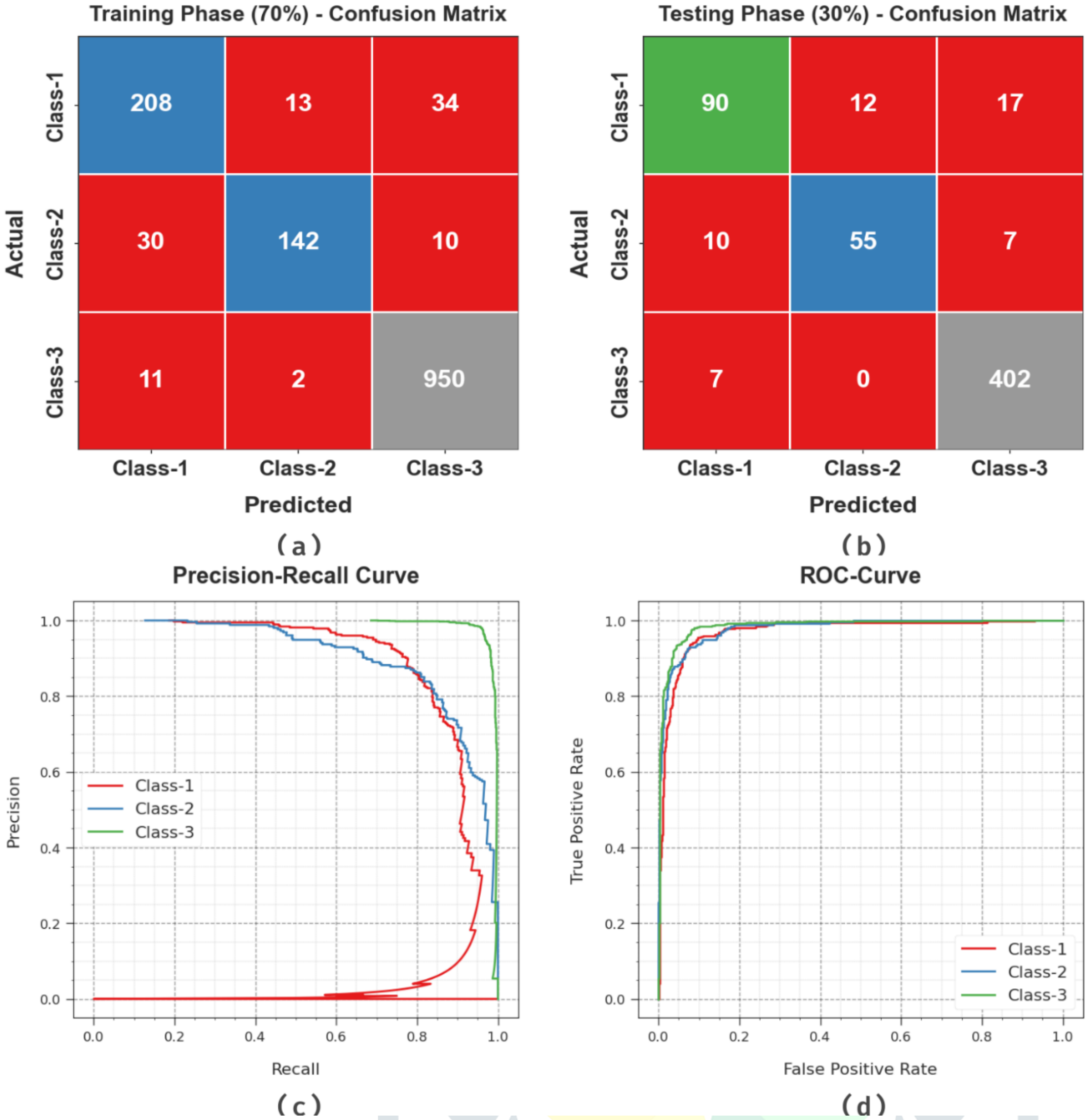

Fig. 2. Classifier outcome of (a-b) Confusion matrices, (c) PR curve, and (d) ROC

In Table 2 and Fig. 3, the skin cancer recognition analysis of the CSADL-SCDDI technique with 70:30 of TR phase/TS phase. The simulated outcome shows that the CSADL-SCDDI system appropriately recognizes three classes. According to 70% TR phase, the CSADL-SCDDI method offers an average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 95.24%, 86.08%, 95.04%, 87.80%, and 83.67% individually. Also, with 30% TS phase, the CSADL-SCDDI methodology provides an average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 94.11%, 83.44%, 93.88%, 85.02%, and 79.86% correspondingly.

Table 2 Skin cancer detection outcome of CSADL-SCDDI approach with 70:30 of TR phase/TS phase

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{score}	MCC
TR Phase (70%)					
Class-1	93.71	81.57	96.42	82.54	78.72
Class-2	96.07	78.02	98.77	83.78	81.84
Class-3	95.93	98.65	89.93	97.09	90.46
Average	**95.24**	**86.08**	**95.04**	**87.80**	**83.67**
TS Phase (30%)					
Class-1	92.33	75.63	96.47	79.65	75.10
Class-2	95.17	76.39	97.73	79.14	76.47
Class-3	94.83	98.29	87.43	96.29	88.00
Average	**94.11**	**83.44**	**93.88**	**85.02**	**79.86**

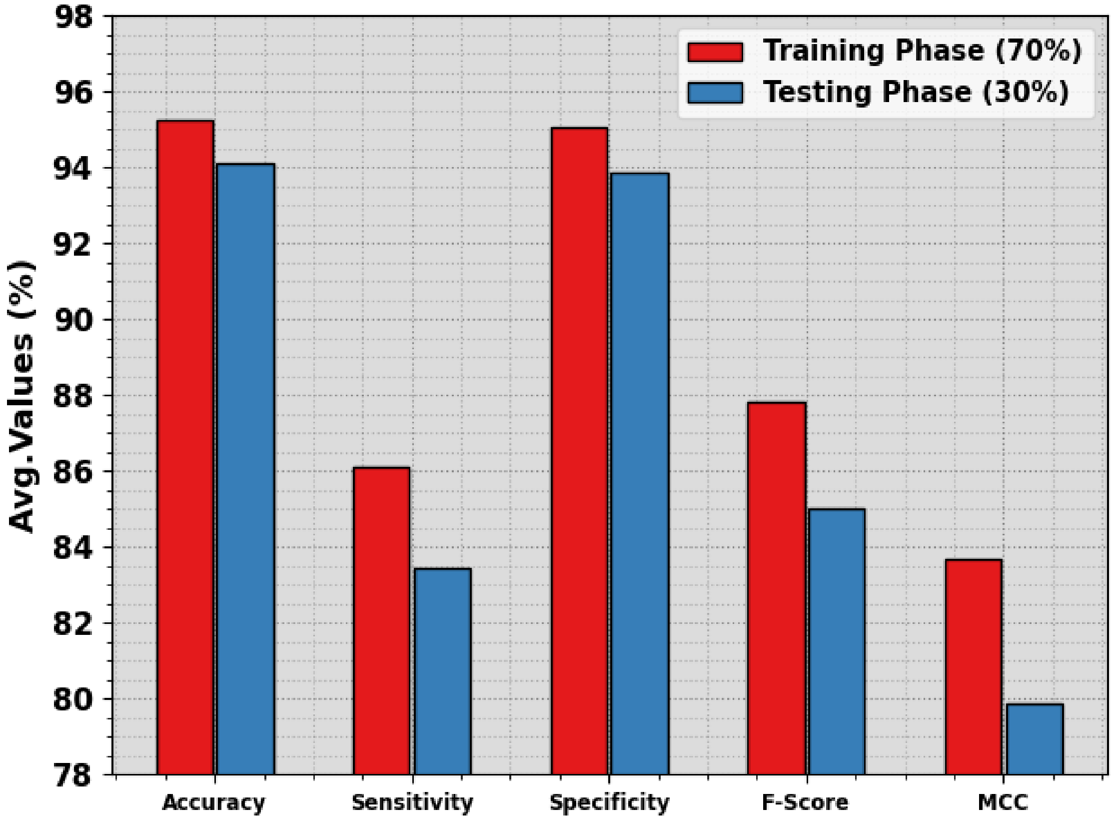

Fig. 3. Average of CSADL-SCDDI approach with 70:30 of TR phase/TS phase

To evaluate the effectiveness of the CSADL-SCDDI algorithm, we have made $accu_y$ curves for the testing (TS) and training (TR) phases, as represented in Fig. 4. Two curves gives valued insights into the model's learning expansion and its capability for generalizing. As we raise the number of epochs, an obvious development in the TR and TS $accu_y$ curves are apparent. This enrichment exhibits the model's potential to higher identified patterns along with the datasets of TR and TS.

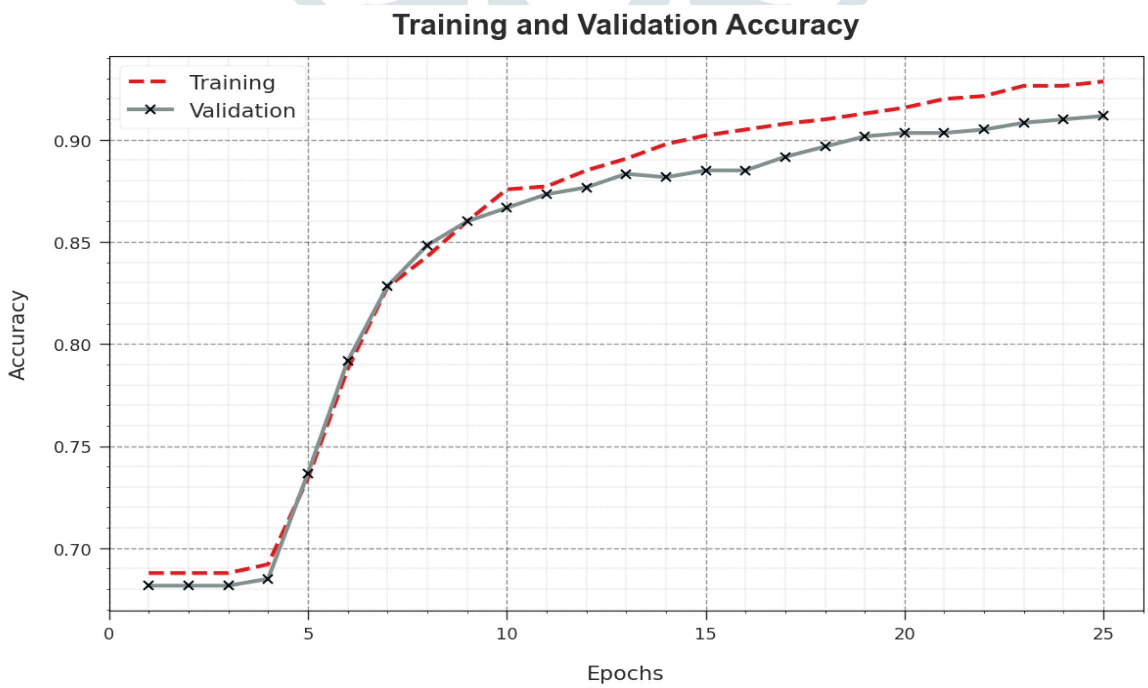

Fig. 4. $Accu_y$ curve of the CSADL-SCDDI approach

To confirm the improvised outcomes of the CSADL-SCDDI system, a comparison analysis is carried out with other existing methodologies, as illustrated in Fig. 5. The achieved value pointed out that the MobileNet model gets worsen outcomes. Additionally, the NB, KELM, MSVM, and DenseNet169 algorithms attains moderately increased performance. Then, the MAFCNN-SCD technique obtains remarkable outcomes. But, the CSADL-SCDDI model gets superior performance with maximal $accu_y$, of 95.27%. The attained outcome conclude that the CSADL-SCDDI approach gains improved skin cancer classification performance.

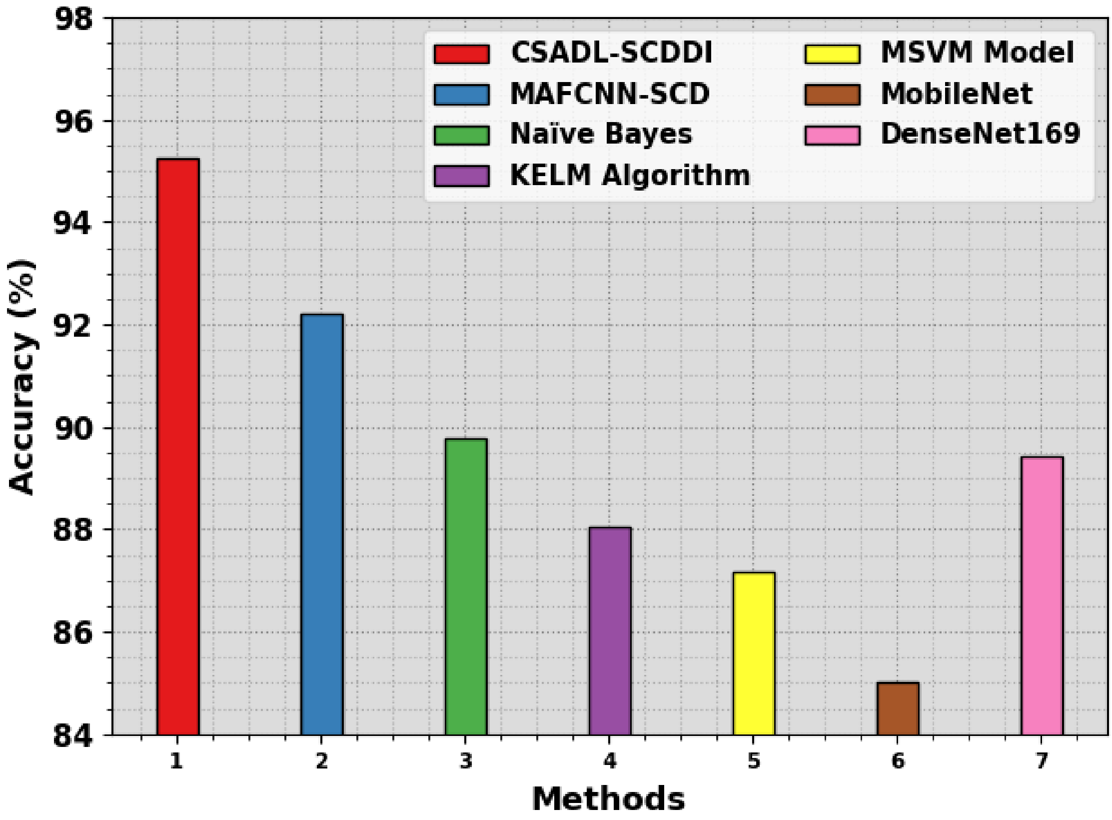

Fig. 5. $Accu_y$ outcome of CSADL-SCDDI model with other existing methods

4. Conclusion

In this study, we focuses on design and developed of CSADL-SCDDI model. We use BF for preprocessing to improve quality of dermatoscopic images. For feature extraction, we influence SqueezeNet technique. The classification step is executed by utilizing RNNs. RNNs are effective and suitable for consecutive data analysis and grab time-based dependencies within feature representations which is perfect for differentiating between benign and malignant skin cancer. To improve the performance of the detection method, we use CSA for parameter tuning. The developed framework is estimated on a huge dataset of dermatoscopic images, representing its efficiency in skin cancer analysis. This complete technique provides excessive ability for the improvement of vigorous and precise skin cancer analytic systems with potential applications in medical settings in order to help dermatologists make decisions on time and more informative.

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