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

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Abstract: ***Skin cancer, a widespread and possibly life-threatening condition, requires an earlier and accurate diagnosis for efficient involvement. Dermoscopic images, providing a window into skin lesions, gives a useful resource for medical specialists in this context. This article goals to develop a complex architecture to detect skin cancer employing dermatoscopy images, integrating cutting-edge techniques in image analysis, machine learning, and artificial intelligence. This manuscript introduces the Dragonfly Algorithm with Deep Learning for Skin Cancer Diagnoses on Dermoscopy Images (DFADL-SCDDI) method. Our technique integrates advanced methods namely feature extraction, preprocessing, classification, and parameter optimization to increase the reliability and of accuracy identification. For image preprocessing, we exploit the Gabor filter (GF), a robust tool for enriching texture and structure data in images. Feature extraction has been executed employing a Capsule Network (CapsNet). CapsNet is a deep learning (DL) model that exceeds in capturing hierarchical and in-depth features in images. Classification is conducted by a Gated Recurrent Unit (GRU), a kind of recurrent neural network (RNN) ability to model sequential patterns and dependencies within the feature representations. To additional improve the model's effectiveness; we implement the Dragonfly Algorithm (DA) for parameter tuning. The DA has a powerful optimization system stimulated by nature, developed for enhancing hyperparameters efficiently, consequently higher the model's diagnostic accuracy. The proposed architecture is assessed on a large database of dermatoscopy images, signifying its effectiveness in skin cancer detection. The outcomes exhibit substantial enhancement in reliability and accuracy compared to traditional systems.***

Keywords: Dragonfly Algorithm; Dermoscopy; Gated Recurrent Unit; Deep Learning; Parameter Tuning

1. Introduction

The most widespread and serious type of cancer in humans is skin cancer. Skin cancer is the condition once the rare growth of the skin cell is uncontrolled. Each day a few of the old skin cells destroyed, and new tissues occupy their location [1]. But, if this method proceeds the incorrect decision, a condition arises once the older cells cannot in the dying phase and then, become dead and new cells develop without requirement for them. The additional amount of skin cells produce the larger tissues then, grow a cancer. To improve the diagnostic technique, dermoscopy is established [2]; it is a non-invasive technique that acquires improved and illuminated images of skin regions [3]. This method could be employed by the dermatologist for skin cancer identification, conventionally executed by visual analysis and manual screening that cannot time-saving and also accurate. Though, the enhancement is achieved in consideration of the new methods of machine learning (ML) in the earliest diagnoses of fatal tumorous diseases [4]. A few skin cancers have been benign and treatable once diagnosed at the earlier phase therefore, it slightly turn into cancer. Melanoma has an extremely severe as well as risky kind of skin cancer [5]. It has various categories of skin cancer and all types of tumor dependent upon the behavior of the irregular cells.

To enhance the efficacy and effectiveness of skin cancer identification automatic diagnosis technique is needed for supporting physicians to increase decision making [6]. For emerging automatic diagnostic tools, standard ML methods are employed for classifying non-melanoma and melanoma [7]. However, it is highly difficult to achieve higher analytical effectiveness because of ML approach is need hand crafted features and dermoscopic images have higher intra-class and lower inter-class differences. Unbiased analysis can be more significant for some earlier identification and treatment of skin cancer diseases [8]. Recently, research workers are considered Convolutional Neural Networks (CNNs) based approaches due to it offers substantially enhanced mining prediction accuracy. Several research workers can be skin cancer classification employing Deep Learning (DL) based algorithms due to their automated feature engineering and self-learning capabilities [9]. With deep neural networks (DNNs) higher performance could be acquired in the expanses of developing the CNN extensive, deeper and improving determination that results in the model having more parameters, which is higher computational efficiency for testing and training [10].

Adla et al. [11] proposed a programmed DL through class attention layer-based CAD technique. Tsallis entropy-based segmentation is utilized for the analysis of affected cancerous areas. Moreover, a DLCAL-based feature extractor was applied in order to remove features from segmented lesions by CAL, CapsNet and Adagrad optimization. Finally, Swallow Swarm Optimizer (SSO) algorithm-based Convolution Sparse AE (CSAE) labelled SSO-CSAE executed for recognition. In [12], proposed a novel DL-IoHT model determined for the detection of skin cancer. Automated features were removed from imageries using many pre-trained methods like Inception V3, SqueezeNet, ResNet50 and VGG19 that delivered into fully connected layers for categorizing skin malignant as well as benign cells. In addition, designed technique is completely combined with IoHT model. Alwakid et al. [13] projected a DL model in order to remove a tumorous region with correctness. Initially, image was upgraded by using an Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) approach. Next, segmentation can be used for dividing ROI from entire image. The author engaged data augmentation in order correct data in contrast. This X- ray image can be additionally performed with CNN and Resnet-50 dataset for classifying skin cancers.

This manuscript introduces the Dragonfly Algorithm with Deep Learning for Skin Cancer Diagnoses on Dermoscopy Images (DFADL-SCDDI) method. For image preprocessing, we exploit the Gabor filter (GF), a robust tool for enriching texture and structure data in images. Feature extraction has been executed employing a Capsule Network (CapsNet). Classification is conducted by a Gated Recurrent Unit (GRU), a kind of recurrent neural network (RNN) ability to model sequential patterns and dependencies within the feature representations. To additional improve the model's effectiveness, we implement the Dragonfly Algorithm (DA) for parameter tuning. The DA has a powerful optimization system stimulated by nature, developed for enhancing hyperparameters efficiently, consequently higher the model's diagnostic accuracy. The proposed architecture is assessed on a large database of dermatoscopy images, signifying its effectiveness in skin cancer detection.

2. The Proposed Model

In this study, we introduce a complete architecture for skin cancer detection dependent upon dermatoscopic images. This method incorporates advanced methods in preprocessing, feature extraction, classification, and parameter optimization for enhancing the accuracy and reliability of identification. Fig. 1 depicts the workflow of DFADL-SCDDI algorithm.

2.1 Preprocessing: Gabor filter

For image preprocessing, we exploit the GF, a robust tool for improving image texture and structure data. By convolution the images with GF, this algorithm effectively increases the data quality by taking texture and structural data [14]. It surpasses in decreasing noise and emphasizing vital image details, mainly in the condition of dermatological images where fine textures and patterns have been essential for accurate detection. The application of the GF substantially increases clarity and structural images, allowing both medical experts and ML approaches to take further specific differences. This preprocessing stage performs a vital function in estimating the accuracy of skin cancer identification, enabling early healthcare interventions, and lastly resulting in enriched patient outcomes within the domain of dermatology.

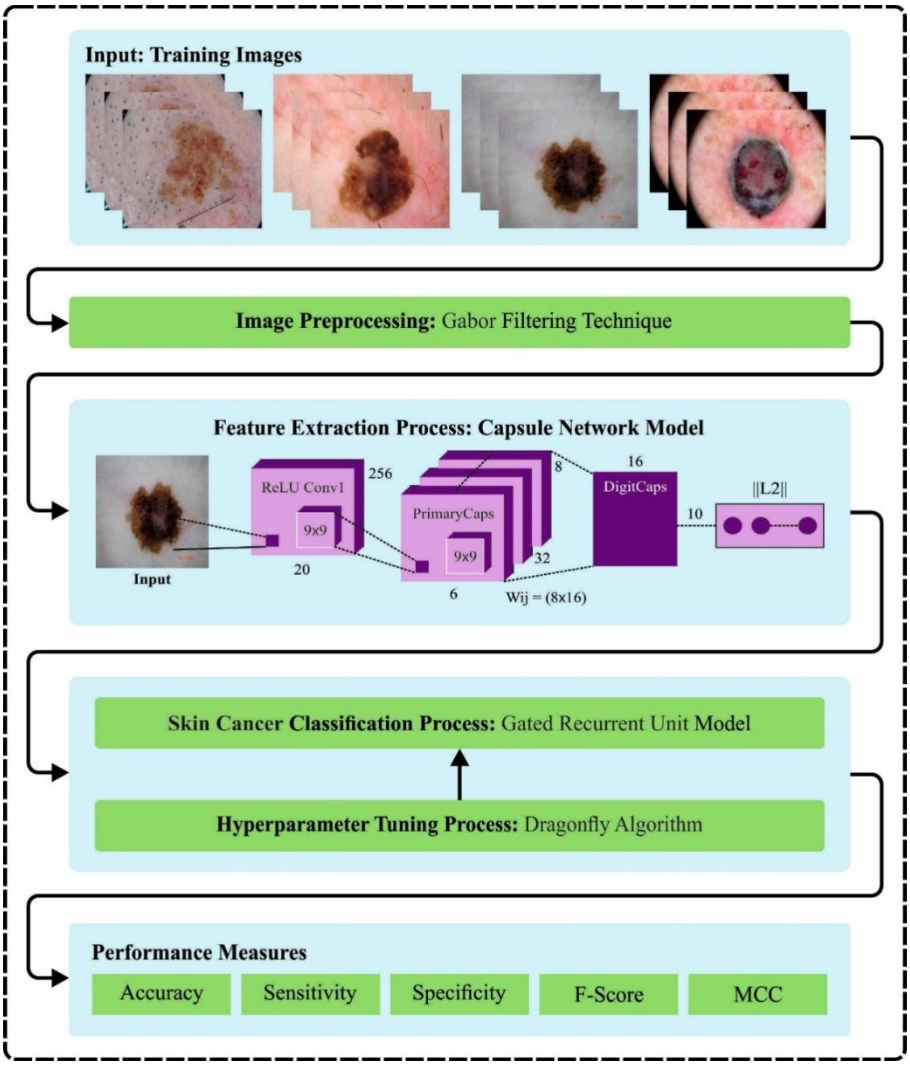

Figure 1: Workflow of DFADL-SCDDI algorithm

2.2 Feature extraction: CapsNet model

Feature extraction is conducted using a CapsNet model. CapsNet's unique framework is particularly developed to take intricate hierarchical features and correlations within images, producing it extremely effective in signifying complex patterns and databases [15]. By utilizing CapsNet for feature extraction, we can produce important, useful representations of data that are mainly valued in tasks like diagnosis of skin cancer. These are extremely descriptive features that can be essential in differentiating subtle nuances within images, resulting in enhanced diagnostic accuracy. CapsNet with its capability to envelop crucial visual data, has developed as a robustness tool in advancing the accuracy of image-based classification processes, eventually providing to highly efficient and reliable as well as improving healthcare within the domain of dermatology.

2.3 Classification: GRU technique

Classification is performed by a GRU. A GRU is resultant from LSTM which has no output gate [16]. The input and forget gate are united into a one gate. In addition, it combines HS and CS into single state. Therefore, GRU is so simple and effective when compared to LSTM. Due to faster and simplicity feature, it becomes more preferable than LSTM. The present hidden state $h(k)$ is considered as follows.

If the data on a preceding HS or input value requires to be rejected, next reset gate $r(k)$ is employed. The data that requires to be kept as well as approved to following step is organized by upgrade gate (k). The insignificant data from prior state that can be disremembered by increasing the reset gate's output by an earlier one. If output of upgrade gate z is near to zero then current state will cover more novel data. But, if output of upgrade gate z is near to one, then the existing data is recalled from earlier time iteration.

Below mentioned are calculations that express the facts clarified overhead at sampling time k:

$$r(k) = \sigma(W_r x(k) + R_r h(k-1) + b_r) \quad (1)$$

$$z(k) = \sigma(W_z x(k) + R_z h(k-1) + b_z) \quad (2)$$

$$g(k) = tanh\left(W_g x(k) + z(k) \times R_g h(k-1) + b_g\right) \quad (3)$$

$$h(k) = \left(1_{n_N \times 1} - z(k)\right) \times g(k) + z(k) \times h(k-1) \quad (4)$$

whereh, z, g and r are said to be candidate activation, upgrade gate, activation function and reset gate separately. And σ is logistic sigmoid function, $and \times is$ an element-wise multiplication. W and R are weight matrixes.

2.4 Hyperparameter tuning: DFA method

To further enhance the model's performance, we apply the DFA for parameter tuning. Mirjalili in 2016 proposed DFA a population-based optimizer approach based on the migration and hunting approaches of dragonfly [17]. The hunting approach is called as feeding (static swarm), where each member of swarm could fly in smaller cluster over the limited space to discover the food source. The migration approach of dragonfly is named migratory (dynamic swarm). In this work, the dragonfly is willing to soar in large cluster, and consequently, the swarm could be migrated. Similar to other swarm-based techniques, the operator of DA implements two major conceptions: diversification, encouraged by the static swarm activity, and intensification, inspired by the dynamic swarm activity.

In DA, five kinds of behaviors are shown below. N indicates the neighborhood size, X shows the location vector, andX_j represents the j^{th} neighbors of X:

- Separation is an approach that dragonfly split itself from others. This process is shown below:

$$S_i = -\sum_{j=1}^{N} X - X_i \quad (5)$$

- Alignment indicates how agent sets its velocity regarding the velocity vector of other adjacent as follows:

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \quad (6)$$

  Here V_j shows the velocity vector of j^{th} neighbors.

- Cohesion represents the inclination of member to move in the direction of adjacent center of mass. This can be expressed as follows:

$$C_i = \frac{\sum_{j=1}^{N} x_j}{N} - X \quad (7)$$

- Attraction indicates the tendency of member towards the food sources. The fascination propensity amongst the i^{th} agents and the food sources are given below:

$$F_i = F_{loc} - X \quad (8)$$

  In Eq. (8), the location of food source isF_{loc}.

- Distraction indicates the dragonfly tendency to retain itself from collision. The disruption amongst the ith dragonfly and the enemy is implemented as follows:

$$E_i = E_{loc} + X \quad (9)$$

Where the enemy's location isE_{loc}.

In DA, the fitness of food sources and location vector is updated by the fittest agent. Furthermore, the fitness value and position of enemy are calculated by the worst dragonfly. This could help DA to converge towards a potential region of the solution space and sequentially, preventing from non-promising area. The location vector of dragonfly is updated by the following sets: the position vector and the step vector (ΔX). The step vector shows the dragonfly direction and it is evaluated by the following expression:

$$\triangle X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + wX_t \quad (10)$$

In Eq. (10), s, w, a, c, f, and e shows the weight vector of dissimilar components.

The position vector of a member is computed by the following expression:

$$X_{t+1} = X_t + \triangle X_{t+1} \quad (11)$$

In Eq. (11), t denotes the iteration counter.

3. Performance Validation

The experimental analysis of the DFADL-SCDDI system is measured on test database. The dataset comprises 2000 samples with three classes as defined in Table 1.

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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**

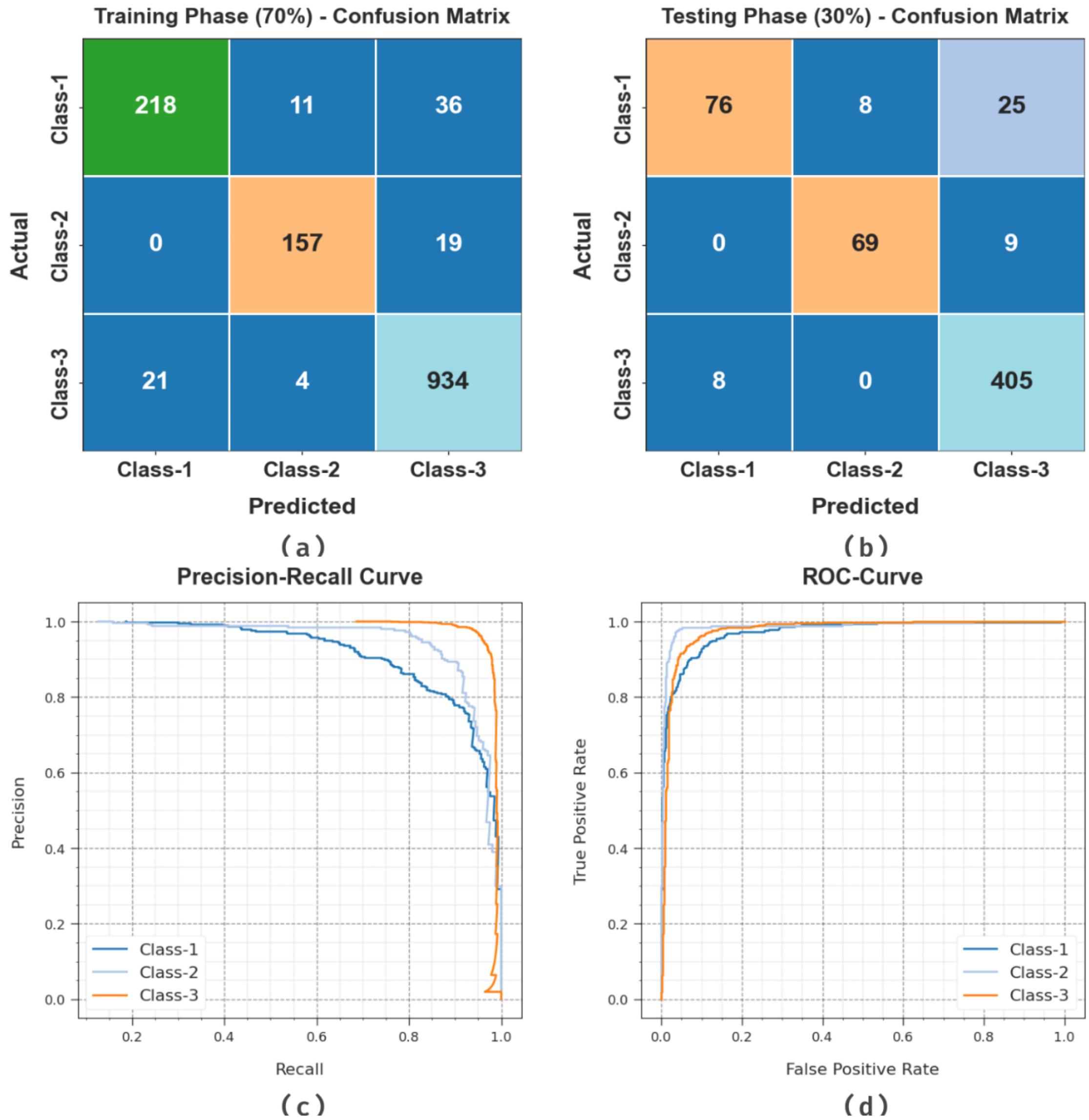

Figure 2: Classifier outcome of (a-b) Confusion matrices, (c) PR curve, and (d) ROC

In Fig. 2 pointed out the classifier analysis of the DFADL-SCDDI system in test database. Figs. 2a-2b exhibits the confusion matrices provided by the DFADL-SCDDI model with 70:30 of TR phase/TS phase. The figure shows that the DFADL-SCDDI method is appropriately recognized and categorized with three classes. Moreover, Fig. 2c represents the PR analysis of the DFADL-SCDDI approach. The figure represented that the DFADL-SCDDI algorithm achieves excellent PR performance with each class. Also, Fig. 2d represents the ROC analysis of the DFADL-SCDDI model. The figure shows that the DFADL-SCDDI methodology accelerates efficient outcomes with better ROC values in diverse classes.

In Table 2 and Fig. 3, the skin cancer recognition analysis of the DFADL-SCDDI system with 70:30 of TR phase/TS phase. The simulated outcome demonstrated that the DFADL-SCDDI technique correctly recognizes three classes. Based on 70% TR phase, the DFADL-SCDDI method gives an average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 95.67%, 89.62%, 94.82%, 90.88%, and 86.40% separately. According to 30% TS phase, the DFADL-SCDDI methodology offers an average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 94.44%, 85.42%, 92.89%, 87.62%, and 82.19% respectively.

Table 2: Skin cancer detection outcome of DFADL-SCDDI systemon 70:30 of TR phase/TS phase

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{score}	MCC
TR Phase (70%)					
Class-1	95.14	82.26	98.15	86.51	83.72
Class-2	97.57	89.20	98.77	90.23	88.85
Class-3	94.29	97.39	87.53	95.89	86.62
Average	**95.67**	**89.62**	**94.82**	**90.88**	**86.40**

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TS Phase (30%)					
Class-1	93.17	69.72	98.37	78.76	75.67
Class-2	97.17	88.46	98.47	89.03	87.41
Class-3	93.00	98.06	81.82	95.07	83.50
Average	**94.44**	**85.42**	**92.89**	**87.62**	**82.19**

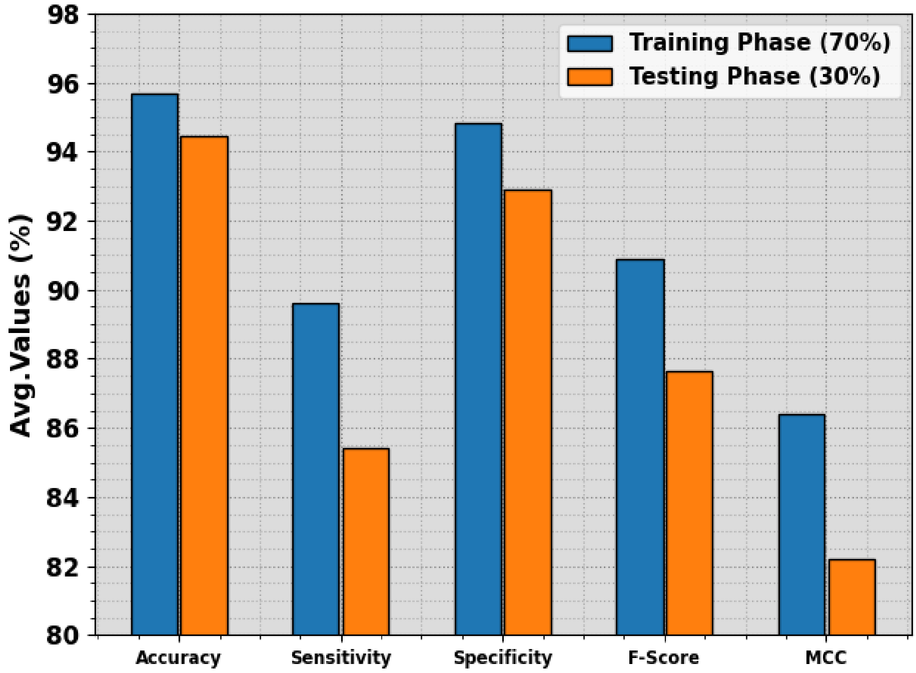

Figure 3: Average of DFADL-SCDDI modelat 70:30 of TR phase/TS phase

To make sure that the enriched outcomes of the DFADL-SCDDI algorithm, a comparison analysis is executed with other existing methodologies, as shown in Fig. 5. The accomplished value indicated that the MobileNet model gets poorer outcomes. Concurrently, the NB, KELM, MSVM, and DenseNet169 algorithms achieve moderately boosted performance. Next, the MAFCNN-SCD system gets remarkable outcomes. However, the DFADL-SCDDI model acquires exceptional performance with greater accu_y, of 95.67%. The obtained outcome determine that the DFADL-SCDDI approach obtains improvised skin cancer classification performance.

Table 3: $Accu_y$ outcome of DFADL-SCDDI model with other existing methods

Methods	Accuracy
DFADL-SCDDI	95.67
MAFCNN-SCD	92.22
Naïve Bayes	89.77
KELM Algorithm	88.04
MSVM Model	87.15
MobileNet	85.03
DenseNet169	89.42

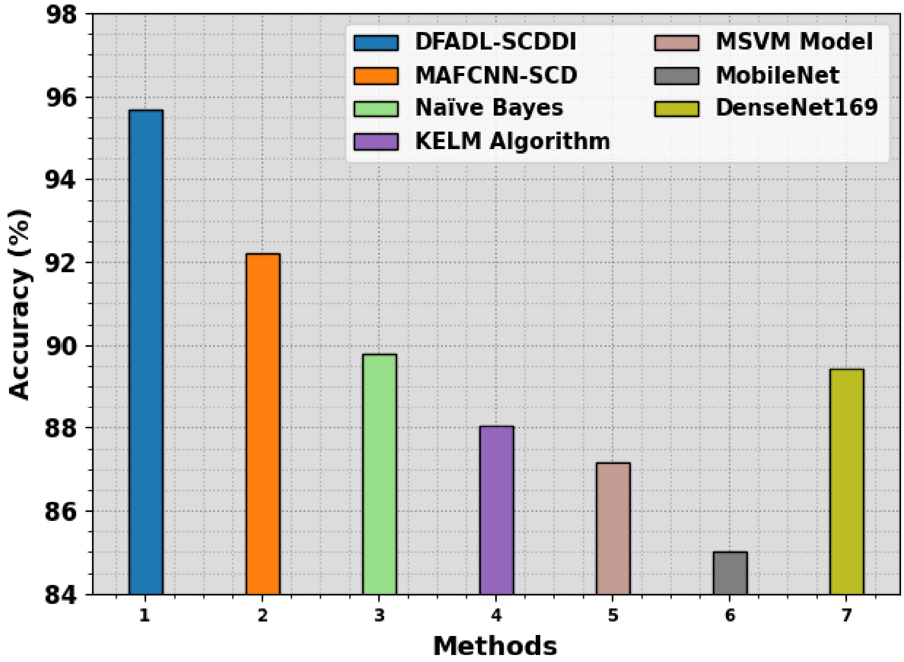

Figure 5: $Accu_y$ outcome of DFADL-SCDDI model with other existing methods

4. Conclusion

In this study, we have offered the design and development of DFADL-SCDDI method. For image preprocessing, we exploit the GF, a robust tool for enriching texture and structure data in images. Feature extraction has been executed employing a CapsNet. CapsNet is a DL model that exceeds in capturing hierarchical and in-depth features in images. Classification is conducted by a GRU, a kind of RNN ability to model sequential patterns and dependencies within the feature representations. To additional improve the model's effectiveness, we implement the DA for parameter tuning. The DA has a powerful optimization system stimulated by nature, developed for enhancing hyperparameters efficiently, consequently higher the model's diagnostic accuracy. The proposed architecture is assessed on a large database of dermatoscopy images, signifying its effectiveness in skin cancer detection. The outcomes exhibit substantial enhancement in reliability and accuracy compared to traditional systems.

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