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# Bootstrapping of fine-tuned segmentation and classification network for epidermis disorder categorization

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**Abstract**
As all people have been affected by various skin related illnesses, categorization of skin disorders has become prominent in recent healthcare system. To identify and categorize skin related syndromes, many transfer learning frameworks were used. Amongst, a Fine-tuned Segmentation and Classification Network (F-SegClassNet) achieved better efficacy by using the novel unified loss function. Nonetheless, it was not apt for the datasets that lack in training images. Hence in this article, Bootstrapping of F-SegClassNet (BF-SegClassNet) model is proposed which solves the imbalanced images in the training set via generating the group of pseudo balanced training batches relying on the properties of the considered skin image dataset. This model fits the distinct abilities of Deep Convolutional Neural Network (DCNN) classifier so that it is highly useful for classifying the skin disorder image dataset with a highly imbalanced image data distribution. According to the Bootstrpping, better tradeoff between simple and complex image samples is realized to make a network model that is suitable for automatic skin disorders classification. In this model, statistics across the complete training set is calculated and a new subset is produced that retains the most essential image samples. So, the skin images are segmented and categorized by this new model to identify the varieties of epidermis infections. At last, the testing outcomes exhibits BF-SegClassNet-model accomplishes the mean accuracy with 96.14% for HAM dataset which is compared to state-of-the-art models.

**Keywords** Epidermis infection · Deep transfer learning · F-SegClassNet · Imbalanced data · DCNN · Bootstrapping

## 1 Introduction

Because of the implications in dealing with illnesses and the discrepancies in varying treatments, epidermis or dermatological illnesses are perhaps the vastest and varied sub-fields of medications. Epidermis infections are known amongst many other illnesses, especially

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those that are quickly transmitted, and can be deleterious to melanoma if not identified in their beginning phases [21]. Skin disorders have risen dramatically in recent years in relation to the proportion of all other kinds of infections [7]. Numerous studies suggest that one-fifth of the population is susceptible to skin problems, making recognition difficult.

As a result, accurate classification of these kinds of illnesses plays an important role by assessing different images including skin lesion morphology, biological pattern interpretation, hue, structuring, and lesion orientation [8]. Depending on a self-governing evaluation of clinical epidermis qualities, identification is exceptionally hard, and epidermis aspects are not derived dynamically. To address such issues, a transfer learning framework was developed to characterize skin infections using pre-trained deep learning formations. Pre-trained models have been primarily used to optimize the weights of deep learning using repetitive back-propagation rather than starting with random weights [15].

Many pre-trained DCNN configurations, such as AlexNet, GoogLeNet, VGGNet, and others, have been used to identify skin problems over the decades [14]. According to this perspective, a 2-phase progressive transfer learning method with a completely monitored Residual Network (ResNet152) model pre-trained on the ImageNet [9] was created for customizing the skin disorder categorization framework on the transitional set. In addition, cycle-Generative Adversarial Network (GAN) knowledge was used as a transfer learning procedure for transforming epidermis characteristics from the input space to the feature space. Despite its high efficiency, DCNN's perceptual insight was ineffective for skin-like visuals. To resolve this concern, epidermis objects were separated using the SegNet, which is a deep encoder-decoder system, and the separated objects were categorised using the DCNN [3]. In contrast, the fine-delineation of the boundaries between the Region-Of-Interests (ROIs) in the skin lesion had not been accomplished.

Thus, a modified SegNet with Categorization known as SegClassNet [11] was created wherein the skin lesion visuals enriched by cycle-GAN have been considered as input. At first, dilated convolution has been used instead of classic convolution to obtain multi-scale contextual elements without deteriorating the image quality. After, the encoder encoded such elements and passed them to the decoder, which was preceded by the dropout layer. The Dynamic Conditional Random Fields (DCRFs) has been used in the dropout layer for resolving overfitting and obtaining the separated skin objects. Moreover, those separated objects have been directly passed to the ResNet18 to categorize the epidermis disorders. Conversely, it employs classical error function which limits the network's ability for training discriminant information from epidermis objects. To solve this problem, an F-Seg-ClassNet [12] was created through modifying the ResNet18's layer using the unified triplet along with the group loss. In this model, the embedding from separated objects was trained into the Euclidean distance by the ResNet18 classifier [5, 13, 17].

The outer skin barrier, often known as the epidermis, is a stratified, self-renewing epithelial layer. Thus, it protects the organism from outside danger like bacterial infections and prevents water loss. This cause can be rectified when identified early and the computational techniques can achieve this, which motivated many researchers.

After, $l_2$ distance was determined among the respective separated objects from Euclidean space to train discriminant information of epidermis objects with the help of unified triplet and group loss functions. Also, the separated objects were categorized by such $l_2$ distances. Even if it employs transfer learning such as cycle-GAN as image augmentation, this model was not appropriate for the datasets that lack in training images.

Therefore, in this paper, BF-Seg Class Net model is presented to resolve the imbalance images in the training set by creating a collection of pseudo balanced training batches depending on the properties of the given skin image dataset. This BF-Seg Class Net model

fits the distinct abilities of DCNNs so that it will be more powerful to categorize the skin disorder image dataset with a highly imbalanced image data distribution. Based on this bootstrapping, a better tradeoff between simple and complex image samples is achieved for creating a model that is appropriate for robust automatic skin disorders classification. In this model, statistics across the complete training set is determined and a new subset called bootstrap samples is created that retains the most essential image samples. Thus, this BF-SegClassNet model addresses that the samples that are chosen as complex by the actual training iterations are crucial for increasing the classification efficiency.

The further paper is emphasized with: The Section 2 investigates works associated with skin disorder categorization. The Section 3 which tells about the BF-SegClassNet model, The Section 4 displays the efficiency. Finally, The Section 5 which will conclude the work and provides future upcoming enhancement.

## 2 Literature survey

In [18] presented the new Gabor wavelet-based DCNN to identify malignant melanoma and seborrheic keratosis. This technique was depending on the decomposing the input images to different directions of sub bands. Then, such images are utilized as inputs for many CNNs parallelly for producing the multiple probabilistic estimations. After, decision merging according to sum policy was applied to categorizing skin lesion. But its accuracy was not effective and the dataset was limited in size.

In [16] designed a hybridized technique to handle the class imbalance of skin disorder categorization. In this technique, level of data scheme of mini-batch logic which are balanced will follow augmentation with the algorithm level, with the real time images to scheme of applying novel loss factor. This technique was utilized with developed Custom Fully Connected Layers (CFCL) with two hidden layers for improving the training efficiency. Also, the batch regularization and dropout methods were employed for enhancing the categorization efficiency. But, it does not able to categorize multiple skin disorders concurrently.

In [4] suggested a modified graph cut technique followed by the probabilistic classification called Naive Bayes (NB) to partitioning skin lesions and categorizing skin disorders. At first, the input images were preprocessed to eliminate the noises and converted from RGB to HSV. Also, threshold was used to smooth and filter the images. Then, these images were partitioned depending on the dynamic boundary update. After that, the features from the infected areas were extracted for categorizing the skin disorders. But, the accuracy of this technique was very less compared to deep learner models.

Al-masni et al. [1] developed a combined diagnostic method which integrates a skin lesion edge segmentation phase and a multiple skin lesions categorization phase. Initially, the skin lesion edges were partitioned from the complete dermoscopy images by the Full resolution Convolutional Network (FrCN). After, different CNN classification models were performed on the partitioned skin lesions to categorize the skin disorders. However, the considered skin lesion images were not adequate. Also, it has high difficulty and cost for the labeling task.

Al-masni et al. [10] introduced an intelligent diagnosis technique which worked digitally, for increasing the accuracy of categorizing many skin disorders. In this technique, a Multi-Class Multi-Level (MCML) categorization method motivated by the divide-and-conquer policy was presented. This technique has four different phases: preprocessing,

partition, feature extraction and categorization. The preprocessing was used to remove the noise, black frame, hair and circle from the skin images. Then, the ROI was partitioned using Otsu's thresholding method and the features were extracted from every ROI. Further, such features were categorized by the MCML to differentiate the skin disorders. However, it needs to optimize the loss function for further increasing the categorization efficiency.

Al-masni et al. [19] designed a Global-Part CNN framework that looks the finely grained local data and the global context data of similar significance. In this framework, Global CNN & some CNN were employed. The G-CNN was learned with images of dermoscopy which were downscaled and utilized for extracting the global-scale data to generate the Classification Activation Map. Also, P-CNN was learned along CAM cropped images and utilized for extracting the local-scale data of skin lesion images. Moreover, data-converted ensemble training was executed to enhance the efficiency of categorization by combining the various discriminant data from GP-CNNs which were learned with color constancy converted images, actual images and feature saliency converted images, accordingly. But it has less sensitivity and accuracy.

Al-masni et al. [2] designed a robust and mobile Deep Neural Network (DNN) which differentiates Herpes Zoster from various skin disorders by utilizing the client-submitted images. In this method, a Knowledge Distillation from Ensemble through Curriculum Training (KDE-CT) was developed in which the student network trains from a robust teacher network progressively. On the other hand, this KDE-CT comprises hyperparameters which need to be automatically optimized based on the considered datasets. Some of the researchers worked on the neural network and structural pruning models [6].

Conclusion Artificial intelligence and machine learning may benefit greatly from neural networks. They have various benefits, including the capacity to generalise and learn from data. They do have some disadvantages, though, such the price and the difficulty in understanding the data. The main benefit of deep learning algorithms, as previously explained, is that they attempt to incrementally learn high-level characteristics from data. This does away with the necessity for hard core feature extraction and domain knowledge.

## 3 Proposed methodology

The BF-SegClassNet-model is explained briefly. Primarily, the dataset of which is collected, and also the multiple-domain adaptation is implemented to the cycle GAN for mapping epidermis characteristics from a source domain (input space) to the target domain (feature space). Afterwards, the modified SegNet is employed for partitioning the skin lesion visuals having high-resolution information. Also, the partitioned images are categorized by the bootstrapping of fine-tuned ResNet18 with Bootstrapping method which enhances the accuracy of identifying the skin disorder categories. Figure 1 portrays a schematic overview of this BF-SegClassNet model for epidermis disorders categorization.

### 3.1 Image acquisition and segmentation

Initially, the HAM10000 data-set are acquired from ISIC archive and accessible as https://isic-archive.com/. Which encompasses 10,015 skin images with 7 various kinds & contains only skin images with 505 of lesions being validated by pathology. Such 7 different kinds of skin disorder images are basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, melanoma, melanocytic nevus and vascular lesion. Then, cycle GAN is

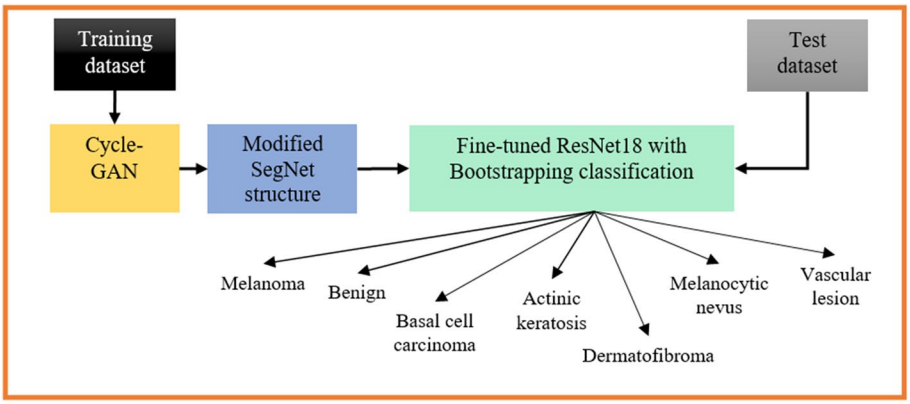


**Fig. 1** Schematic overview of epidermis disorders categorization using BF-SegClassNet model

implemented for mapping the skin lesion qualities from input space to the feature space. These images are then given to the modified SegNet for splitting the diseased ROIs from every image. Once the ROIs are split, then DCNN such as ResNet18 with Bootstrapping is executed to classify the skin disorder categories. Figure 2 illustrates the structure of BF-SegClassNet model for epidermis disorders categorization.

### 3.2 DCNN with bootstrapping classification

Generally, the execution of DCNN directly on a skewed dataset results in ineffective categorization i.e., the prediction error rates during the convergent task may highly fluctuate or increase when applying DCNN on an imbalanced dataset. Since during learning, DCNNs partitions the training set into multiple batches. On the other hand, if partitioning an imbalanced dataset, few of such batches may include no positive sample but only

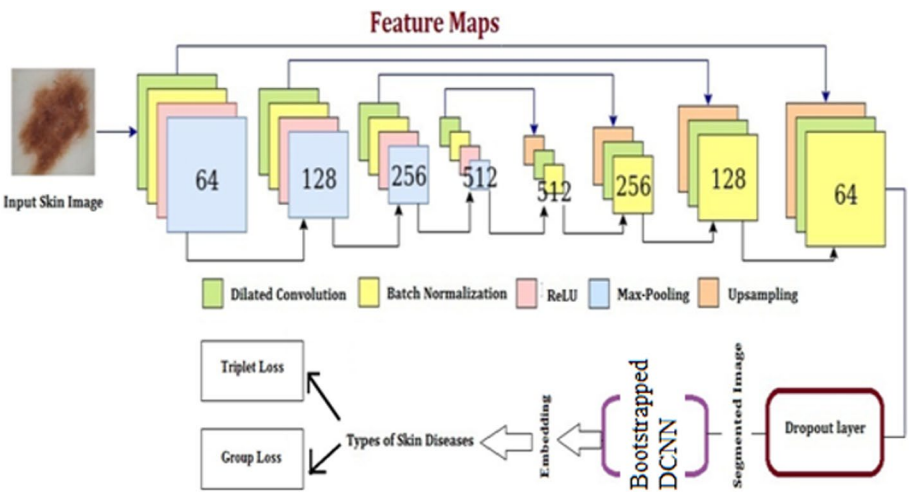


**Fig. 2** Structure of BF-SegClassNet for epidermis disorder categorization

negative samples because of the skewed distribution of the training set. So, this trained DCNN execute weakly if applied to the testing set.

To combat this challenge, the DCNN is improved with the bootstrapping sampling scheme. In this model, the SegNet output i.e., the partitioned ROIs is utilized to bootstrap and initialize the skin disease related pixels (features) for training the DCNN model. Consider $x$ and $y$ are the amounts of negative and positive samples, accordingly, in the imbalanced training set with $x \gg y$. In this proposed model, every batch is generated with the equal dimension $z$ ($z = z_x + z_y$) and the equal negative to positive rate $u$ ($u = z_x/z_y$) where $z_x$ and $z_y$ are the amounts of negative and positive samples. Absolutely, $B$ batches are created were,

$$B = \lfloor {}^{x}/_{z_x} \rfloor \tag{1}$$

In other terms, if $z_x$ is not appropriately divisible by $B$, any leftover negative samples are discarded in the training task. Because the overall number of negative samples $x$ in the training set is large and batch size $z$ is commonly small (so $z_x$ is small), the negative samples being discarded is insignificant than the ones applied in the training task. After, a positive sample is chosen randomly from $y$ positive ones for $z_y$ times and those are combined with $z_x$ negative samples for all batches. This procedure is performed totally $T$ ties for creating batches in all training iterations. Such a random procedure guarantees that every positive sample has a same opportunity to be selected and learned with several negative samples to prevent overfitting. In all iterations, the bootstrapping task creates a pseudo balanced training set from the actual imbalanced image dataset. Further, this model is utilized for learning the DCNN (ResNet18) classifier to identify the epidermis disorder categories.

Consider the dimension of all inputs is $x*y$. A scenario of 4 mid-layer DCNN is illustrated in Table 1, where $k_L$ is the number of neurons that apply on a small batch of inputs and $x_L*x_L$ is the dimension of all neurons in the $L^{th}$ convolution layer. The outcome of $L^{th}$ convolution layer is provided to the $L^{th}$ pooling layer and is split into a group of non-overlapping rectangles of dimension $p_L*p_L$, where the pooling process is performed for down-sampling.

In this model, the low-level features are fed to the DCNN rather to highly decrease $y$ value and to enhance the efficiency of categorization. Given the input image, the bootstrapping scheme is employed for creating $B$ batches of balanced training images that are given to the CNN's first layer i.e., input layer regularly in iterations. Following the input layers, there are 2 convolutional layers. Every layer is preceded by its corresponding max-pooling layer. The initial convolutional layer uses $k_1*x_1*x_1$ neurons on the input and creates their inner product as the outcome. The outcome is considered as the input for the initial max-pooling layer. Its outcome is the input of the second convolutional layer, preceded by the

**Table 1** Training parameters for DCNN

| Layer | Layer dimension | Outcome dimension |
|---|---|---|
| Input ($x*y$) | | |
| Convolution 1 | $k_1*x_1*x_1$ | $k_1*(y-x_1+1)*(y-x_1+1)$ |
| Pooling 1 | $p_1*p_1$ | $k_1*(y-x_1+1)/p_1*(y-x_1+1)/p_1$ |
| Convolution 2 | $k_2*x_2*x_2$ | Consider $y_2=(y-x_1+1)/p_1$; $k_2*(y_2-x_2+1)*(y_2-x_2+1)$ |
| Pooling 2 | $p_2*p_2$ | $k_2*(y_2-x_2+1)/p_2*(y_2-x_2+1)/p_2$ |
| Outcome | | 7 |

max-pooling layer applying similar procedure but with various neuron dimensions. The dimension of the resultant DCNN outcome is the amount of skin disorder types i.e., 7 to which the image is categorized. Once each $B$ batch is learned, the resultant convolution neurons and weights are utilized for categorization. The testing sample is allocated to the class with the maximum outcome score. Therefore, the efficiency is improved on testing set once completed the rounds of bootstrapping.

Consequently, the bootstrapped training sets are produced until the learning error converges to a minimum. But the error does not reduce on the test set and rather obtains a fluctuating efficiency at every bootstrapping round. To realize this fact, the error is averaged for similar samples that contributed towards the enhanced training in the initial bootstrapping iteration. Observe that such samples may be occurred in a various error bin at a dissimilar bootstrap iteration. This fluctuation nature is in agreement with different break-even points in the test set at various bootstrap iterations. This fact occurs since this model initiates to change the simple and complex samples at all iterations of the bootstrapping. If the real complex samples are utilized for learning during bootstrapping, the efficiency relapses to the enhanced state.

This scenario is experienced for the initial time after sampling from primary learning and observable at the second iteration of bootstrapping. Thus, the complex samples acquired after real learning handle the efficiency on the testing set.

Algorithm for the F-SegClassNet -Model:

Divide $NEG$ into $B$ batches, every batch with $z_x$ negative samples;

$\boldsymbol{for}(1{:}\,T)$

$\boldsymbol{for}(1{:}\,B)$

$\boldsymbol{for}\left(1{:}\,z_y\right)$

Choose a sample randomly from $POS$;

$\boldsymbol{end\ for}$

Merge the $POS$ and $NEG$ samples together;

$\boldsymbol{end\ for}$

Train the fine-tuned ResNet18-based DCNN classifier;

$\boldsymbol{end\ for}$

Categorize the varieties of epidermis disorders;

**End**

## 4 Experimental results

The performance of BF-SegClassNet-model is evaluated through implementing it in Python 3.7.8. From the HAM dataset [20], 70 percentage of the skin lesion visuals among all classes which are utilized by training and the remaining 30 percentage from all classes are utilized for testing. Also, the performance is evaluated with the classical models

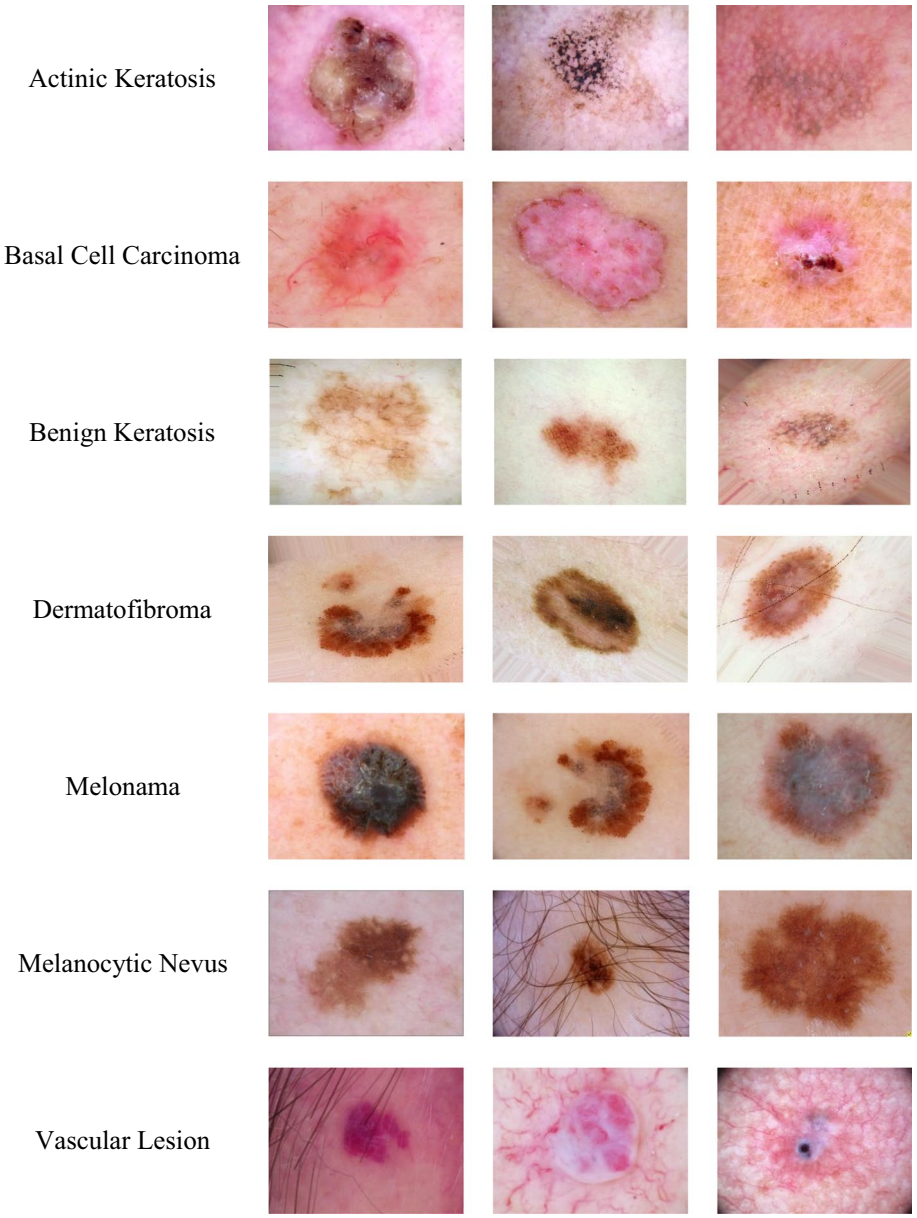


**Fig. 3** Sample input images for various kinds of epidermis infections

depending on f-measure precision, accuracy and recall. The example of the input images from HAM dataset of all skin disorder categories are given in Fig. 3.

Precision is calculated as:

$$Precision = \frac{No.of\ perfectly\ classified\ melanoma/benign\ images}{No.of\ perfectly\ classified\ melanoma/benign\ images + No.of\ imperfectly\ classified\ melanoma/benign\ images} \tag{2}$$

Recall is calculated as:

$$Recall = \frac{No.of\ perfectly\ classified\ benign/melanoma\ images}{Number\ of\ perfectly\ classified\ \ benign/melanoma\ images + Number\ of\ imperfectly\ classified\ benign\ images} \tag{3}$$

"F measure" is calculated by

$$F - measure = 2 \times \frac{Recall * Precision}{Recall + Precision} \tag{4}$$

Accuracy is calculated as:

$$Accuracy = \frac{True\ Negative\ (TN) + TP}{FP + TP + TN + FN} \tag{5}$$

The comparison outcomes of precision, recall, f-measure and accuracy for ResNet-152 [9], SegClassNet [11], F-SegClassNet [12], Gabor wavelet-DCNN [18], GP-CNN [19] and BF-SegClassNet implemented on HAM dataset are listed in Table 2 and shown in Fig. 4.

This testing finding observes that the BF-SegClassNet-based categorization model provides a greater performance than various models. Epidermis disorder categorization model is concerned, BF-SegClassNet model is highly useful for accurateness.

## 5 Conclusion

Finally, BF-SegClassNet was presented by using the bootstrapping method integrated into the deep learner for enhancing the classification accurateness. First, the ROIs from input skin images were partitioned using the chamged SegNet. Then, integrated from each ROI is mapped to the Euclidean space based on the bootstrapped ResNet-18 model. In this classification, the statistics across the entire training set was computed and a novel subset was created that retains the most essential image samples. Also, the collection of pseudo balanced training batches was generated to solve the imbalanced training sets challenge. As a result, the unique behavior of DCNN classification is enhanced

**Table 2** Findings of various epidermis disorder categorization models on HAM dataset

| Evaluation Metrics | Gabor wavelet-DCNN | ResNet-152 | SegClassNet | GP-CNN | F-SegClassNet | BF-SegClassNet |
|---|---|---|---|---|---|---|
| Precision (%) | 79.96 | 88.40 | 90.94 | 92.55 | 93.26 | 95.98 |
| Recall (%) | 80.62 | 88.68 | 91.22 | 92.64 | 93.31 | 96.03 |
| F-measure (%) | 80.33 | 88.56 | 91.04 | 92.60 | 93.28 | 96.01 |
| Accuracy (%) | 80.57 | 88.78 | 91.28 | 92.71 | 93.37 | 96.14 |

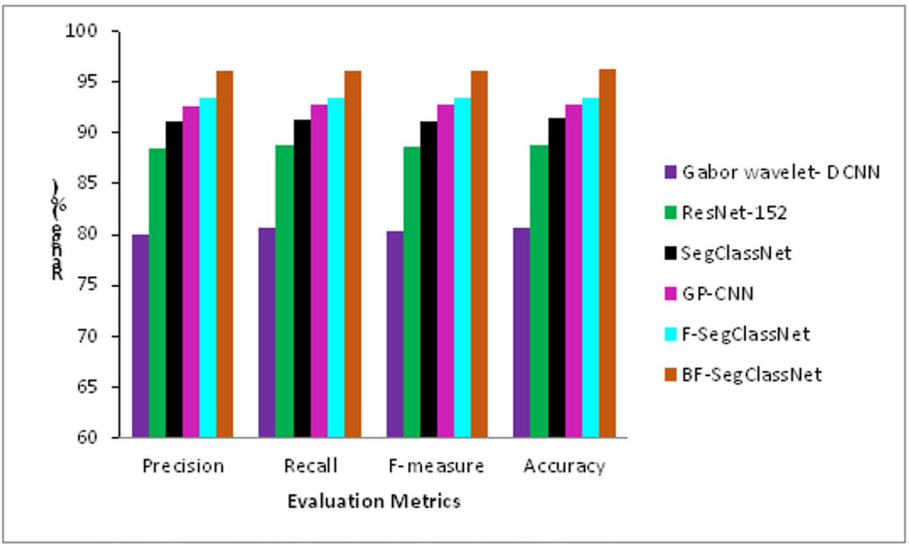


**Fig. 4** Analysis of evaluation metrics on HAM10000 dataset

to categorize the epidermis disorder varieties. Eventually, the findings revealed that the BF-SegClassNet gains the accuracy rate of 96.14% for HAM dataset while average accuracy of Gabor wavelet-DCNN, ResNet152, SegClassNet, GP-CNN and F-SegClassNet are 80.57%, 88.78%, 91.28%, 92.71% and 93.37%, correspondingly. Although it solves the imbalanced dataset problem, the drawback of cycle-GAN becomes dramatic when the source domain varies greatly from the feature space. Therefore, the upcoming research will concentrate on finding the solution to the knowledge transfer in dynamic circumstances.

## Declarations

**Conflict of interest** The authors declare that we have no conflict of interest.

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