Skin Lesion Analysis Toward Accurate Detection of Melanoma using Multistage Fully Connected Residual Network

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***Abstract*—Automatic classification of skin disease is a challenging task due to high similarity among them as well as complex nature of skin images i.e. hair, skin and nails and illumination conditions . It is one of the most common malignancy that becomes more difficult to treat and potential disfigurement or even death, if not diagnosed early. In this paper, we present a fully automatic skin lesion classification by leveraging three stage deep residual neural networks that is trained end-to-end and does not rely on prior knowledge of the data. Extensive experiment on ISIC-2018 challenges shows that our methods showed considerable improvement (96.07%) in the classification of skin melanoma by not only super-passing the ISIC-2018 challenges as well state of the art methods.**

***Index Terms*—Skin Cancer, Melanoma, Residual Network, ISIC Challenge**

I. Introduction

The skin constitutes considerable portion of an individual that contributes 16% weight of whole body. It covers an area of about 20 square feet. The skin is composed of three layers i.e., epidermis, dermis, and subcutaneous tissues also known as hypodermis. The main tasks of skin are thermoregulation, metabolism, sensation, protection. The skin is an impediment against the external invasions that protect the individual's body. The skin contains blood vessels, lymphatic vessels, nerves, and muscles, which cause sweat through the pores, maintains the outside degrees, and shield the body [1]. The skin disease may cause due to exposure in extreme sun shine, heat and cold, chemicals and drugs etc.

The *Dermatology* is regarded as the most unsure and difficult branch of medical sciences because complex process involved in detection of diseases related to hair, skin and nails. This becomes further complicated with different types of skin color and different skin diseases. The symptoms of skin disorder are rash, scaly, dry or cracked skin, and open lesions etc. The Skin disease is most complicated and the irritating disease effecting almost all ages of people. More than two thousand skin diseases have been recognized and the number increases with each passing day. Almost 80% of the people are suffering from some kind of skin diseases. If these diseases are not addressed in time then it may lead to complicated results.The *Melanoma* is considered as most intricate type of skin disease which may leads to individual's expiration. Early detection and surgery of the melanoma gives the patient 99% chance of survival rate for 5 years [2]. It is of great significance to detect skin diseases correctly and prescribe medicines or any other treatment afterwards because any misjudgment may lead to serious damage to the skin. In todays era of scientific development it becomes easier to suggest the proper method for the identification of diagnosed skin diseases. International Skin Imaging Collaboration (ISIC) along with other global partnership is working on development of efficient methods for early detection of skin cancer. The ISIC-18 is the largest skin image analysis challenge in the world and has organized the world's largest public repository of dermoscopic images of skin. Recent challenges attracted researchers attention and received over 900 registrations and over 350 submissions, making them the largest standardized and comparative results at the time, yielding findings with significant gain in performance.

Recently, many researchers focuses on the problem of identifying different diseases using deep learning and they got excellent rate of skin cancer identification [3]. Recent ISIS challenge witness the success of deep learning for skin lesions over other machine learning methods. In this study, we present the deep neural network for the classification of skin cancer and compared with state of the art methods. Though, dermatologists can visually examine the suspicious spot and may suggest biopsy if required to confirm the presence of cancer. However, computer-aided diagnosis of skin cancer can help to detect cancer much early with high accuracy even without visiting a clinic.

Recently, deep learning has shown remarkable performance in different fields [4]–[6]. ISIC challenges witness the success of deep learning methods for classification of skin cancer. One of the recent system developed by Stanford University for skin cancer detection using CNN on a large dataset consisting of 129,450 clinical images. Deeper networks are hard to train due to the notorious vanishing gradient problem as the gradient is back-propagated to earlier layers thus, repeated multiplication may make the gradient infinitely small. As a result, with the increase of network depth, its performance gets saturated or even starts degrading rapidly. In this paper, we used the concept of identity shortcut connection that skips one or more layers to avoid the problem of vanishing gradients, by reusing activation from a previous layer until the adjacent layer learns

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its weights. To validate the performance of multistage fully cconvolutional network, we have used HAM10000 dataset consisting of 10015 training images that showed considerable improvement with 96.07% accuracy outperforming ISIC-2018 and ISIC-2017 skin cancer competition.

The key contributions of this work are:

- We present multistage fully connected deep residual neural network by leveraging three stage deep residual neural networks that is trained end-to-end and does not rely on prior knowledge of the data.
- Classes are not represented equally in ISIC challenge. To handle an imbalanced class problem, in this work we have performed sampling of minority classes.
- Extensive experiment on ISIC-2018 challenge shows considerable improvement in classification performance skin lesion by competing winner of ISIC-2018 competition.

The remaining paper is organized as follows.The background is analyzed in section II, whereas section III describes the related work. Section IV presents dataset used. Section V describes methodology. Section VI summarizes the results and their analysis. Consequences and future directions are figured in Section VII.

II. Related Work

For years, dermoscopy is widely used technique in the diagnosis of skin lesions. Ideally, dermatologist can accurately identify the malignant tumor at the early stage; however, receiving such intensive screening is not possible practically for each patient. With the increase in incidence of skin tumors, it has become an important to identify it at early stage to avoid the potential disfigurement or death. To develop computer-aided diagnostics, in 1994, Binder et al [15] first used dermoscopic images to differentiate between the types of skin lesions. Recently, many researchers focuses on the problem of identifying different diseases using deep learning and they got excellent rate of skin cancer identification. Recent ISIS challenge witness the success of deep learning for skin lesions over other machine learning methods. MetaOptima's secured first three positions in ISIC-18 melanoma classification task[1]. The CNN models are ensembled with a stacking scheme [16] and achieved 0.801 balanced accuracy on seresneXt-50 and balanced multi-class accuracy of 0.885. The same authors. In another work, ranked at second at ISIC challenge, authors used meta ensemble approach and got 0.801 balanced accuracy on seresneXt-50 and balanced multi-class accuracy of 0.882 [16]. Another work that ranked at 3rd place in the competition, has used best single model approach and got 0.801 balanced accuracy on seresneXt-50 and balanced multi-class accuracy of 0.871.

Lopez et al. [7] presented a deep learning approach for classifying melanoma. They used VGG16 architecture. ISBI 2016 Challenge dataset were used for experiments. After under sampling of final dataset, they disintegrate the dataset into 346 training images and 150 test images. The proposed method shows better results with sensitivity value of 78.66%. Mishra et al. [8] suggested a deep learning method build on U-Net architecture for automatic melanoma detection. Experiments are performed on ISIB 2017 challenge dataset where 2000 images were set for training and 750 for validation and testing. Their proposed method achieved a jaccard index of 0.842 and has accuracy of 92.8% which outperforms recent methods. Guo et al. [11] presented multiple CNN to classify seven types of skin lesion. They used ISIC 2018 dataset for training and validating the model. There are 10015 training images, 193 validation and 1512 test images. The results shows accuracy of 0.99 for training and 0.72 on validation. Pal et al. [12] suggested an aggregation of deep CNN for classification of seven different types of skin lesions. The HAM10000 dataset is used in which there are 10015 training images. They used only 10% training images as validation set and classify by using the architectures Resnet50, densenet121 and mobile net. ResNet50 got 77.3%, DenseNet got 69.8% validation score, MobileNet got 59.7% validation score. An ensemble of MobileNet and DenseNet achieved 71.5% validation score, ensemble of DenseNet and MobileNet achieved 71.5% validation score, ensemble of ResNet50 and MobileNet achieved 77.1% validation score and ensemble of ResNet50, DenseNet and MobileNet achieved highest validation score of 77.5%. Salido et al. [13] proposed a deep learning approaches for the automatic detection of melanoma. Preprocessing is done to remove hairs etc. and then lesion is segmented and later done the classification. They used Ph2 dataset. They used a dataset split of 70-10-20. Images are trained using pretrained model Alexnet and achieved an accuracy of 93% along with 86% sensitivity and 94% specificity. Unlu and Cinar [17] proposed deep neural network for skin images binary classification. They used dataset taken from ISIC containing 1483 training images and 517 test images. They used pre trained state of art model AlexNet and achieved an accuracy of 81%. Hameed et al. [18] proposed multi class skin diseases classification using deep CNN and support vector machine SVM. They use the dataset taken from different sources consisting of total 9144 images, 6402 training images while 2742 are test images. Alexnet is used along with the SVM classifier and got an accuracy of 86.21%. Ray [14] suggested skin disease classification using deep learning model Resnet. They used the dataset extracted from the "ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection". Features were extracted using Resnet model and classified using deepforest. Compared to state of art methods, better results achieved. They got 97.15% training accuracy and 80.04% test accuracy. Mirunalini et al. [9] suggested deep learning method for the classification of skin lesions. Images were preprocessed i.e. resizing, mirrored, cropped, scaled and increasing brightness. Raw data is collected from different sources containing 2000 training images, 150 validation images and 600 test images. Google's Inception-v3 model was used and achieved AUC score of 65.8% on validation set. Kwasigroch et al. [10] proposed a deep neural methods for classifying

[1]https://challenge2018.isic-archive.com/leaderboards/

TABLE 1
Summary of deep learning based methods for skin disease detection

–	Preprocessing	Dataset	Learning model	Results (%)
Lopez et al. [7]	Normalization, cropping, resizing	Dermquest dataset (126 images), ISBI 2016 (900 training images and 379 test images)	VGG16	78.66 (sensitivity)
Mishra et al. [8]	bilinear interpolation, Gaussian lters for smoothing	ISBI 2017 (2000 training images, 150 validation images, 600 test images)	U-Net	92.8 accuracy 84 jaccard index
Mirunalini et al. [9]	Resizing, mirrored, cropped, scaled and increased in brightness	Experimental dataset (2000 training images, 150 validation images, 600 test images)	Inception-v3	65.8 AUC (validation set)
wasigroch et al. [10]	Scaling, upsampling, data augmentation	ISIC Dataset (Train set: 9300 benign and 670 malignant images, test: 100 images)	VGG19, ResNet50, VGG19-SVM	81.2 Accuracy, 95 Sensitivity, 68 Specificity 75.5 Accuracy, 90 Sensitivity, 61 Specificity 80.7 Accuracy, 93 Sensitivity, 69 Specificity
Guo et al. [11]	—	ISIC 2018 dataset (10015 training images, 193 validation images, 1512 test images)	MCNN	99 accuracy (training) 72 accuracy (validation)
Pal et al. [12]	—	HAM10000	Ensembling of Resnet50, DenseNet121 and MobileNet	77.5 Accuracy (validation)
Salido and ruiz [13]	Morphological operation for hair removal	Ph2 dataset 200 images (70% training, 20% testing, 10% validation)	AlexNet	93 Accuracy, 86 sensitivity, 94 specificity
Ray [14]	Image resizing	extracted from the "ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection"	ResNet50	97.15 accuracy (Training), 80.04 accuracy (Test)

skin lesion. Preprocessing like scaling, upsampling, data augmentation is done. They used the dataset created by the International Skin Imaging Collaboration consisting of 9300 training benign images and 670 training malignant and 100 test images. VGG19, Resnet and VGG19 SVM were used and by using VGG19 81.2% Accuracy, 95% Sensitivity and 68% Specificity achieved. By using ResNet50 they got 75.5% Accuracy, 90% Sensitivity and 61% Specificity. VGG19-SVM results are 80.7% Accuracy, 93% Sensitivity and 69% Specificity. M. Li et al. [19] designed a pipeline for a lesion boundary segmentation and lesion diagnosis task using modern convolutional neural network. They used HAM10000 dataset in which there are 10015 training images. They used 80-20 split for experiments. First, the features are extracted by using ResNet50 and then Mask RCNN is used for lesion boundary segmentation. ResNet, DenseNet and Inception were used for lesion diagnosis purpose. Results are not mentioned. Deeper networks are hard to train due to the notorious vanishing gradient problem as the gradient is back-propagated to earlier layers thus, repeated multiplication may make the gradient infinitely small. As a result, with the increase of network depth, its performance gets saturated or even starts degrading rapidly. Residual network has been used to overcome the issue of network depth, however, still unable to consider the low level features, thus in this work we present block ResNet with each layer receives feature maps from all preceding layers in each block as a result the network can be thinner and compact, thus the number of channels can be fewer.

III. Dataset

International Skin Imaging Collaboration (ISIC) has developed the ISIC Archive, an international repository of dermoscopic images, for both the purposes of clinical training, and for supporting technical research toward automated algorithmic analysis by hosting the ISIC Challenges. The goal for ISIC challenge is to improve melanoma diagnosis through the accessibility of data in order to enhance early detection and reduce the amount of unnecessary biopsies. The objective is to classify dermoscopic these images among different diagnostic categories (7 and 9 in ISIC-2018 and ISIC-2019 challenge). The ISIC released HAM10000 dataset for training and evaluation [20]. The dataset consists of seven classes (i.e., Actinic Keratosis (akiec), Basal Cell Carcinoma (bcc), Benign Keratosis (bkl), Dermatofibroma (df), Melanoma (mel), Melanocytic nevus (nv) and Vascular lesion (vasc) with 327, 514, 1099, 115, 6705 and 142 number of images respectively) with total number of 10015 training images.

More than 50% of lesions have been verified by pathologist, while the ground truth for the rest of the lesions was either follow-up, expert consensus, or conrmation by in-vivo confocal microscopy. More than 95% of all lesion

encountered during clinical practice will fall into one of the seven diagnostic categories [20].

TABLE II
Statistical Analysis of HAM10000 original and upsampled dataset (Number of images in each class)

Disease	Origional	Up Sampled
akiec	327	6705
bcc	514	6705
bkl	1099	6705
df	115	6705
mel	1113	6705
nv	6705	6705
vasc	142	6705
Total images	10015	46935

IV. Deep Skin Lesions Classification

Skin disease analysis has always been a challenging task for researchers due to high similarity among them as well as complex nature of skin images i.e. hair, skin and nails. Traditional methods failed to provide dermatologist-level classification of skin cancer. Recent ISIS challenge witness the success of deep learning for skin lesions over other machine learning methods. ResNet is network of a kind that builds on constructs known from pyramidal cells in the cerebral cortex. Residual neural networks simulate this concept by utilizing skip connections, or short-cuts to jump over some layers, thus, it makes possible to train up to hundreds or even thousands of layers and still achieves compelling performance. It is based on identity mapping that promote the gradient propagation. To adjust the model capacity, the number of independent paths are used, that helps to improve the performance over the deep or wider network, thus still suffer from complex feature learning as it does not consider collective knowledge from preceding layers. To overcome the aforementioned challenge, in this study, we present the deep neural network for the classification of skin cancer by leveraging multistage deep residual neural networks that is trained end-to-end and does not rely on prior knowledge of the data. Figure 1 shows the architecture of proposed framework for Melanoma classification. Unlike ResNet, We adopt the residual learning in each block as well as consider the features from earlier layers within each block locally as shown in figure 1 that results learning collective knowledge from all preceding layers as well as substantial deeper than ResNet and its counterpart. Since every layer in each block receive input features from its all preceding layers thus, the network has few number of channels in comparison as result it will be compact and thinner. We further uses the projection shortcuts when the dimension changes especially while shifting from one stage to other stage. In case of projection shortcuts, it still perform the identity mapping, however with additional zero padding with increased dimension.

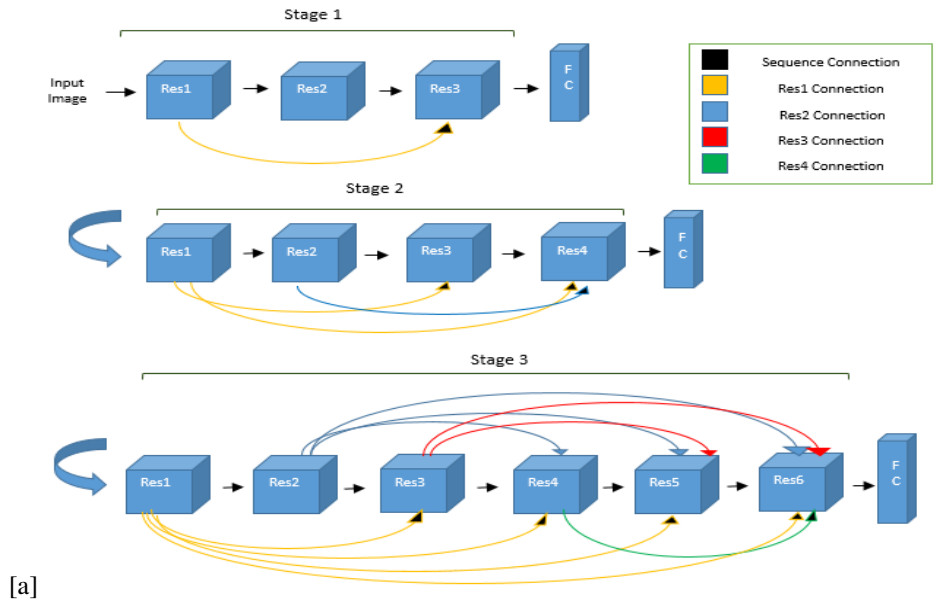
A. Up-sampling and Data Augmentation

Table II describe the HAM10000 dataset class distribution that shows the classification of skin lesion is extreme imbalance problem, which will will bias the prediction model towards the more common classes such as Melanocytic nevus, melanocytic nevus and benign keratosis. To resolve the issue of imbalance class problem, in this work, we have used up-sampling approach to balance the samples in each class. We performed up-sampling by replicating the samples from minority classes and equals the numbers as in majority class. Table II shows that melanocytic nevus contains highest samples. We replicates samples in all other classes to make it equal to 6705 samples. We further performed data augmentation such as random cropping, random vertical and horizontal flipping, rotation and shear up to 90 and 20 respectively, as well as color (contract, saturation and hue). We resize each image in the dataset to 224×224 size.

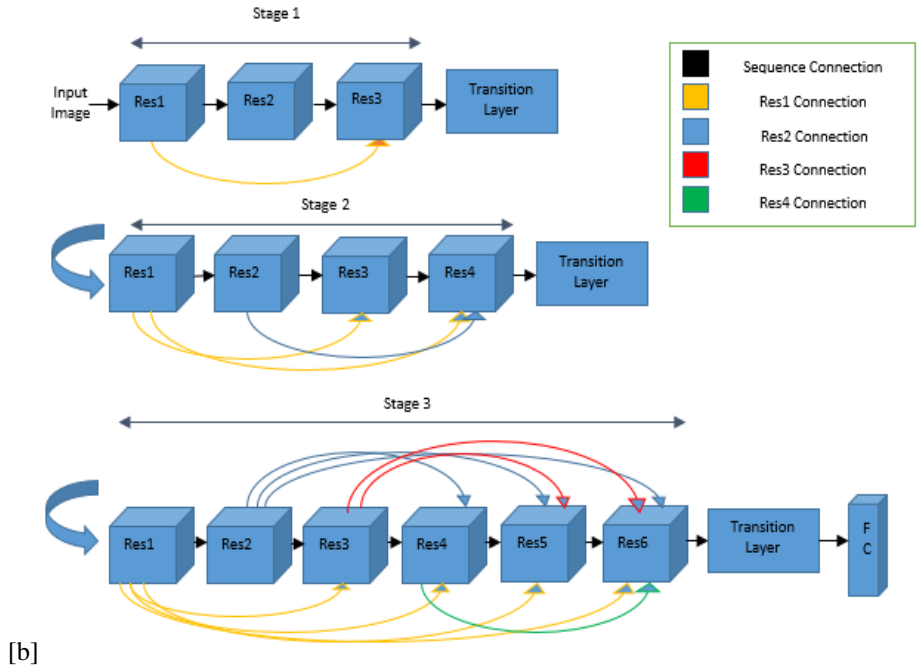
B. Multistage Fully Connected Deep Residual Network

ResNet is network of a kind that builds on constructs known from pyramidal cells in the cerebral cortex. Residual neural networks simulate this concept by utilizing skip connections, or short-cuts to jump over some layers, thus, it makes possible to train up to hundreds or even thousands of layers and still achieves compelling performance, however, it does not consider collective knowledge from preceding layers. To overcome the aforementioned challenge, in this paper, we presented multi-stage fully connected residual based architecture as shown in figure 1 that uses the identity shortcut connection thus skips one or more layers to avoid the problem of vanishing gradients, by reusing activation from a previous layer until the adjacent layer learns its weights. Unlike ResNet, We adopt the residual learning in each stage as shown in figure 1 that results in substantially deeper than ResNet and its counterpart. Since every layer in each block receive input features from its all preceding layers thus, the network has few number of channels in comparison as result it will be compact and thinner. We further uses the projection shortcuts when the dimension changes especially while shifting from one stage to other stage. In case of projection shortcuts, it still perform the identity mapping, however with additional zero padding with increased dimension. The training of deep network is affected by the flow of control and gradients, FcResNet solves this issue through the use of fully connected layer and uses only identity shortcuts when the input and output are same within each stage. We further uses the projection shortcuts when the dimension changes especially while shifting from one stage to other stage. In case of projection shortcuts, it still perform the identity mapping, however with additional zero padding with increased dimension.

FcResNet consists of multiple dense stages with a fully connected layer in each stage i.e. each stage is a mini dense residual network. Stage 1 consist of series (3x) of convolution layers of size 1x1,3x3,1x1 filters with the kernel size of 64,64,256 respectively followed by a fully connected layer. Notice that the residual block function has same dimensions, thus does not requires change in dimension for dense identity shortcuts between ResNet blocks. Similarly, stage 2 consist of consist of series (4x) of convolution layers of size 1x1,3x3,1x1 filters with the kernel size of 128,128,512 respectively fol-



[a]



[b]

Fig. 1. Proposed multistage fully connected residual network (a) Without Transition (b) With Transition

TABLE III
Results of different architectures on HAM10000 Dataset using Up sampled dataset

Architectures	Accuracy (%)	Sensitivity/ Recall (%)	Specificity (%)	Precision (%)	F-Score (%)
FcResNet	92.34	92.34	98.72	92.18	92.15
FcResNet with Transition layer	96.07	96.41	96.02	96.00	96.07

lowed by a fully connected layer. This series is repeated with different kernel sizes at each stage. The number of kernels are constantly increasing in each stage. After this, an average pooling layer with a filter width of 1 is used before the fully connected layer as well as before the softmax layer. In first stage, there are three mini residual blocks. Each block is connected to the next as well as to all the succeeding blocks. For example, Res1 is connected to Res2 and Res3 also in

stage 1. Similarly, in stage 2, 4 mini residual blocks are there and each mini block is connected to the next as well as to all the upcoming blocks. For example, Res1 is connected to Res2 and also connected to Res3 and Res4 in stage 2. Finally in 3rd stage, there are 6 mini residual blocks and each mini block is connected to the next as well as all the remaining blocks. At the end of each stage, we used transition layer which has 1x1 convolutional layer and 2x2 average pooling layer (as shown in Figure 1.b).

V. Experiments

In this section, we described the experimental setup and evaluation of the multistage fully connected deep residual network. To validate the effectiveness of the proposed network, we extensively evaluated the network performance on ISIC-2018 dataset on different parameters and compared the performance with state of the art methods especially top performer of ISIC-2018 competition. Table III shows the performance of the proposed system.

TABLE IV
Comparison of Skin Disease Identification system on ISIC-2018 Challenge

Authors	**Models**	**Results (%)**
Kassani et al. [21]	ResNet50	92.08
Milton et al. [22]	PNASNet-5-Large model	76
Hagerty et al. [23]	Fusion (Hand crafted, deep learning)	94
Reddy et al. [24]	ResNet50	91
Pal et al. [12]	Ensemble of resnet50, densenet121 and mobilenet	77.5
Hekler et al. [25]	Fusion of CNN + dermatologist	82.95
Proposed	FcResNet	92.34
Proposed	FcResNet-TL	96.07

A. Parameters

FcResNet architecture consists of multiple dense stages with a fully connected layer in each stage i.e. each stage is a mini dense residual network. Stage 1 consist of series (3x) of convolution layers of size 1x1,3x3,1x1 filters with the kernel size of 64,64,256 respectively followed by a fully connected layer. Each stage consists of a number of mini dense residual blocks. Each min residual block consists a number of convolutional layers followed by batch normalization and ReLu layer. The mini residual block consist of series of 1x1, 3x3, 1x1 convolution layers and shortcut connection to the activation function. We initialize the weights as in [26] and train the network from scratch. To find the best parameter, we trained the network on different parameters of each residual blocks. We set the learning rate to (1 x 10^{-4}) and momentum of (0.9). The training was stopped when there was no improvement in the error rate of the validation set for 30 epochs. The number of kernels are constantly increasing in each stage.

B. Results and Discussion

This section describes the experimental evaluation of the strategies proposed fully connected multistage residual network for the classification of skin cancer. To achieve optimal performance of the proposed FcResNet, We have performed several experiments with not only different block number but also with different ResNet parameters in each stage. In order to achieve best results and select optimal number of ResNet unit in each stage, we have performed several experiments with a variable number of residual blocks and various number of mini ResNet in each block. The comparison with ISI-2018 challenge and state of the methods is shown in Table IV. The contributions are ranked using primary matrix values (balanced multi-class accuracy). MetaOptima's, secured first three position in ISIC-18 melanoma classification task [2]. The CNN models are ensembled with a stacking scheme [16]. To improve the classification performance by increasing the training set, authors combined multiple proprietary and publicly available skin cancer detests and trained number of different pre-trained (trained on ImageNet) networks with varying architectures. Authors have applied different data augmentation techniques such as random rotations, brightness, saturation and contrasts. The challenge of imbalance class is address through mini-batch as well as inverse frequency is used to determine the weight of loss function. Researcher from the DAISYLab ensemble pre-trained (trained on ImageNet) Densenet, SENet, SE-Resnet, PolyNet and ResNeXt and secured fourth position in competition [27]. Authors have used loss weighting and balanced batch sampling to deal with imbalanced class problem. Research from medical image analysis group (ranked five and rank 6) presented ensemble of SENet and PNASNet-5-Large. The pre-trained (ImageNet) ensemble CNN achieved 0.845 and 0.824 primary matrix values. Our proposed approach showed significant gain (0.891) in primary matrix value in comparison to the first five position holder 0.885, 0.882, 0.871, 0.856 and 0.845 . Similar behaviour can be notice in other evaluation parameters, i.e., FcResNet-TL/Winner 0.984/0.983 (AUC), 0.9601/0.958 (accuracy), 0.964/0.833 (sensitivity), 0.960/0.986 (specificity), 0.960/0.826 (precision) and 0.9607/0.823 (dice). Table V shows the further detail comparison with top 5 positions of ISIC-challenge.

From the Table IV and Table V, we can notice that not only FcResNet has beaten the winner of ISIC-2018 challenge but also showed significantly better performance in comparison to the dermatologists. During the clinical examination of the patient, the dermatologists can not perform visual inspection of affected area but also have access to additional information available for diagnosis such as location of melanoma, patient age and skin color etc. that can help in decision making to achieve better identification. Haenssle et al. suggest that aid of clinical can can slightly improve the sensitivity and specificity of dermatologists [28] which was further validated by Heklet et.al. by improving the performance though fusion

[2]https://challenge2018.isic-archive.com/leaderboards/

TABLE V
COMPARISON WITH ISIC COMPETITION

Approach	Primary Metric Value*	AUC	**Accuracy** (%)	**Error Rate** (%)	**Sensitivity** (%)	**Specificity** (%)	**Precision** (%)	**F-Score** (%)
Winner-2018	0.885	0.983	0.958	0.042	0.833	0.986	0.826	0.823
Runner Up-2018	0.882	0.982	0.960	0.040	0.835	0.986	0.838	0.831
Rank 3	0.871	0.980	0.954	0.046	0.830	0.981	0.794	0.805
Rank 4	0.856	0.987	0.972	0.028	0.809	0.984	0.841	0.841
Rank 5	0.845	0.978	0.968	0.032	0.804	0.980	0.830	0.830
FcResNet-TL (Proposed)	0.886	0.984	0.961	0.393	0.964	0.960	0.960	0.961

of dermatologists decision with deep learning results [25].

Thus, we suggest that the classification performance of skin cancer can be further improved by adding the clinical data with imaging data such as patient age, gender, anatomic location especially patient race and skin type) and dataset should consist of additional patient information along with imaging data. Further research and development on such dataset is thus required to improve classification efficacy. Table IV depicts the comparison of state-of-art with the proposed CNN and Table V shows the comparison with ISIC-2018 challenge.

VI. CONCLUSION

In this work, we presented novel fully connected multistage deep residual convolutional neural network for the classification of skin lesions. FcResNet is multistage deep residual neural networks that provide the direct access to the gradients from the loss function and the input feature map in each residual network. The experimental results obtained on ISIC-18 challenge are significant (0.886) in comparison to ISIC-2018 top five results i.e. 0.885, 0.882, 0.871, 0.856 and 0.845. We have noticed the similar trend for other evaluation parameters, i.e., FcResNet-TL/Winner 0.984/0.983 (AUC), 0.961/0.958 (accuracy), 0.964/0.833 (sensitivity), 0.960/0.986 (specificity), 0.960/0.826 (precision) and 0.961/0.823 (dice). Results suggest that proposed network showed the significantly better performance for the classification of seven types of skin lesions.

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