SkinAid: A GAN-based Automatic Skin Lesion Monitoring Method for IoMT Frameworks

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***Abstract*—Not knowing the type of skin lesion or too much-delayed diagnosis can lead to chronic disease or skin cancer. In SkinAid, we propose an application that can not only assist the dermatologist in obtaining a preliminary analysis of detecting, classifying and monitoring the skin lesion but also creates awareness for the user to care for the skin. SkinAid classifies and provides information on several skin lesions. In this regard, the highly unbalanced and limited data leads the existing Deep Learning models to overfit or poorly generalize, resulting in reduced performance. We explore Generative Adversarial Networks (GANs) to augment and enhance the dataset. Also, we trained a Deep Convolutional Neural Network (CNN) model for edge computing platforms that can automatically detect and classify skin lesions from the captured image of the user's skin. A single-board computer and a smartphone employed as edge platforms have been implemented in SkinAid. The SkinAid model detects and classifies 7 different skin lesions with an overall accuracy of 92.2%. A health worker or patient can capture the real-time skin lesion images using a smartphone app camera to obtain a preliminary analysis to diagnose the skin lesion in Internet-of-Medical-Things (IoMT) platform for remote monitoring by dermatologists.**

***Index Terms*—Smart Healthcare, Internet of Medical Things (IoMT), GAN, CNN, skin lesion, Deep Learning.**

I. Introduction

The term "Skin Lesion" refers to those patches of skin that appear deviant from the rest of the skin. Some visible examples of deviants include irregular coloring of skin and itching. Skin lesions are classified into many classes based upon different characterizations and properties of lesions. Broadly lesions are classified as Benign and Malignant. [1]. Some examples of malignant lesions include Melanoma [2] and Basal Cell Carcinoma, while benign lesions include Melanocytic Nevi, Actinic Keratosis, etc. Malignant lesions are cancerous and are sometimes life-threatening.

However, many lesions go unidentified or unrecorded due to many factors [3]. Statistics show that number of people diagnosed with cancer-causing skin lesions is estimated to be 9500 per day in the United States. The average cost of treating skin cancers in the United States is, projected to be 8.1 billion dollars. Studies by dermatologists depict that most skin lesions are harmless, but there is a need to classify these lesions rapidly for early diagnosis. According to a survey by the Skin Cancer Foundation, 99% of skin cancers can be cured by early detection.

In the new age of Deep Learning and Computer Vision, frameworks provide the best possible solutions to tackle this problem. But one of the significant shortcomings of these frameworks is the deficiency of data. Due to numerous skin lesions and different variants in different people, there is always a deficiency of skin data. ISIC, HAM10000, PAD-UFES are some of the significant datasets of skin lesions [4]. Though they are claimed to be state-of-the-art datasets, they still lack data on certain classes of lesions. In recent years, CNNs were proven to produce the most accurate and precise results for developing skin-lesion classifiers [5]. The main objective of using deep neural networks is their ability of learning to extract features very effectively.

Benign lesions like Actinic Keratosis, Melanocytic Nevi, Benign Keratosis, Vascular Lesions, Dermatofibroma, and Malignant Lesions like Melanoma [6] and Basal Cell Carcinoma are the seven types of skin lesions detected and classified through this research. A Wasserstein GAN is used to generate synthetic data by training on the original data for each class exclusively, and finally, a CNN is trained to detect and classify skin lesions. Our concept revolves around developing a mobile application that takes a skin lesion image as input and classifies the image into the respective lesion class using a trained CNN model. This work proposes SkinAid, an IoMT-enabled mobile application that could detect and classify 7 different skin lesions from images captured with a Smartphone. The major contributions of our work includes the following:

- The presence of essential image preprocessing techniques to enhance the process of feature extraction.
- Generation of synthetic data by training the Wasserstain GAN with gradient penalty.
- Training a CNN architecture with the (synthetic data + original data) thus obtaining an improved and higher

accuracy as compared to other works.

- A robust user-friendly android application that can assist healthcare professionals is developed in obtaining a preliminary analysis by detecting and classifying the skin lesion on real-time data.

The paper is organized as follows: Section II gives the overview of prior related work. Section III emphasises upon the methodology of designing the Skin Aid framework. Section IV discusses about the experimental results and the hardware specifications of the proposed system.

II. Related Research Overview

Cancer-causing skin lesions are increasing rapidly, early identification and classification of these different kinds of skin lesions have always been a matter of contention among different researchers.

The significance of IoMT Smart healthcare is that there is effective diagnosis of different potential diseases, proper treatment of these diseases and improvement in the quality of life. Currently, research in IoMT Smart healthcare is seen as a multi-dimensional scenario where many parameters are taken in account. Some examples of research in this field include human body monitoring, stress monitoring and Food in-take monitoring [7] [8].

But some of the existing works in skin lesion classification are limited to binary classification, i.e., Non-melanoma (non-cancerous) or Melanoma (cancerous), and data augmentation techniques were also absent, with the sole use of the under-sampling technique, resulting in over-fitting and poor generalization [9]. A method combining deep CNNs and traditional computer vision features based on clinical criteria with unbalanced and limited data is proposed in [10]. However, the model achieved a maximum training accuracy of only 85.5%.

Fusing the deep features from various pre-trained CNNs is shown to lead to better classification performance in [11]. But it was restrictive to only 3 skin lesions and included only AlexNet, VGG-16, and ResNet-18 as their pre-trained models while there were many state-of-the-art CNN architectures. A new prediction model based on a new regularizer was presented in [12], which achieved high accuracy. However, it was limited to binary classification, and choosing the regularization parameter was difficult as mentioned by the author.

Although extensive research has been conducted in this field, to the best of our knowledge, none of these solutions has a preprocessing pipeline with cropping contours, global contrast normalization and morphological transformations. None of solutions used advanced data augmentation techniques like GANs for generating synthetic data. Most of them do not have a dedicated user interface like a smartphone application built with the trained deep learning model for practical real-world use.

The SkinAid not only ensures that it is detecting the class of skin lesion captured from the smartphone camera but additionally, it also generates a preliminary analysis in the form of a report and provides information and awareness about the diagnosed lesion. Table I shows the comparison of SkinAid with existing solutions of skin lesion classification.

III. Proposed Novel SkinAid in an IoMT Framework

SkinAid provides the patient with a mobile app that can be used to detect and classify skin lesions by exploiting the computation power and digital lens of smartphones. This forms the next wave of advancement in smart skincare. The outline of the proposed approach is shown in Fig. 1 and subsequently, it is explained in detail in the following sub-sections.

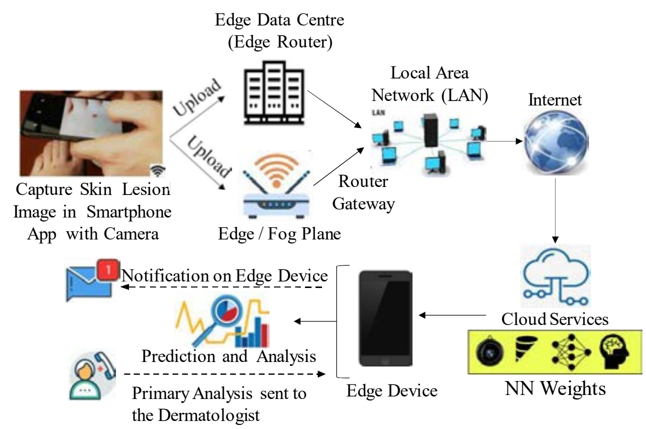


Fig. 1. Proposed IoMT based H-CPS for Smart Healthcare with SkinAid

The methodology is organized in the following fragments:

- **Data preprocessing:** The data is pre-processed to remove unnecessary noise and redundant background which might reduce the classification performance. The techniques used for preprocessing are contour detection and cropping, GCN, and morphological Transformations.
- **Generation of new samples:** By training the W-GAN on the limited data, new synthetic samples are generated to overcome limited and unbalanced data challenges. This enhances the data as we train the CNN model in the next section.
- **CNN Training:** A robust CNN model is trained, validated and tested with an improved accuracy. Further, the model is converted into a .pb file for android deployment.
- **Deployment:** The trained weights of our model are deployed in an android application using JAVA. A user-friendly interface is designed. Skin lesion image can be captured and the app classifies the lesions into its respective class and provides preliminary analysis and information about the lesion.

A. Dataset

In this paper, we used the HAM10000 dataset, which is a collection of various skin lesions and dermatoscopic images. The HAM10000 dataset consists of 10,015 skin lesion images with 7 different classes of lesions, and this dataset is publically accessible [13]. Unfortunately, it is limited and has highly unbalanced classes, and if directly trained on CNN architectures, it would over-fit and fail to generalize, leading to

TABLE I
COMPARISON OF SKINAID WITH EXISTING WORKS

Name of the Work	Methodology Used	Dataset	Accuracy	Interface Present?	Over-fitting?	No. of Lesions Classified
Skin Lesion Classification from Dermoscopic Images [9]	VGGNet	Dermofit Image Library	81.3%	No	No	2
Deep Learning Feature Combining Classification [10]	Modified ResNet50	ISIC 2018	85.5%	No	No	7
Skin Lesion Classification using Hybrid NNs [11]	SVM Classifiers	ISIC 2017	83.3%	No	Partial Over-fitting	2
Skin Lesion Classification Using Convolutional Neural Network With Novel Regularizer [12]	Novel Regularizer	ISIC Archives	97.2%	No	No	2
SkinAid	**WGAN-GP with DenseNet-121**	**HAM-10000**	**92.2%**	**Yes**	**No**	**7**

poor performance. To address this problem, we preprocessed the entire dataset and split it into training and test sets. Then we use the training set to train the W-GAN and generate synthetic data, thereby increasing and augmenting our training data thus, overcoming the highly unbalanced classes and limited data challenges. Finally, we combine the synthetic samples and training sets and split into train and validation sets. Next we train on different CNN architectures, validate and test the architectures, and deploy our best model in the Smartphone application.

B. Image preprocessing

The images present in the dataset are not uniform there is a presence of noise and unnecessary background which implies the presence of undesired features. The significance of image preprocessing is that it reduces the noise and other factors leading to misclassification to a great extent.

Contour Detection: In a broader perspective, contours are referred to as a drawn outline of an irregular figure. In our context, they refer to the outlines of the skin lesion. Here we use contours, for detecting lesions in the images to extract the region-of-interest (ROI), including only the skin lesion pixels, thereby excluding the unwanted background. This reduced a lot of time taken by manual cropping. We aim to determine the bounding box of the lesion in its minimum enclosed area. The $cv2.findContours$ function in conjunction with another few OpenCV utilities makes this very easy to accomplish. Further, all the images were resized to $(224 \times 224 \times 3)$ since they had different dimensions. Algorithm 1 depicts the above process.

Algorithm 1 Algorithm for Contour Detection and Extraction of ROI

Input: Image
Output: Contours
  for img in os.imgdirectory() **do**
    if $(img \neq None)$ **then**
      img = cv2.imread(image path)
      grey = img.cvtColor(RGB to Grey)
      Thresh-Image = cv2.threshold(grey)
      Contours = cv2.findContours(Thresh-Image)
    end if
  end for
  return Contours

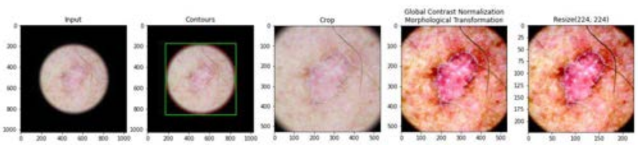
Global Contrast Normalization: In image processing, contrast is referred to as the luminance difference between bright and dark pixels that makes an object distinguishable in an image. Some images can have high contrast and some can have low contrast, which results in losing important features and having compact information in images respectively. Therefore, we apply global contrast normalization by calculating the mean of an image and subtracting it from each pixel, and then divide each pixel by the standard deviation. All these calculations and operations are implemented using Numpy in python. This helps in improving the performance of our model with better feature extraction.

Morphological Transformation: Generally, while capturing images, there is always a chance that image pixels could be spatially disconnected, though it makes a minor fragment of the image to be noisy. This problem can be solved using morphological transformation. Here two functions of morphological transformation are useful they are dilation and erosion. Dilation helps in connecting adjacent pixels by turning on the pixel value, and erosion does the reverse. Thus, using the dual of dilation and erosion simultaneously is considered an efficient technique for noise reduction.

The outcome of image preprocessing is depicted in Fig. 2. In order to perform the above task, a sample image from the dataset is taken which is shown in Fig. 2a. Subsequently, Figures 2b, 2c and 2d show the preprocessing steps. Finally, Fig. 2e shows the results of image resizing.

C. Data Augmentation with WGAN:

Due to the highly unbalanced classes and limited data of original skin lesion images in our dataset, it is prone to over-fitting and poor performance if directly trained on CNNs. Therefore, we decided to use data augmentation techniques



(a) Sample image from HAM10000 dataset
(b) Contour detection with OpenCV to extract Region-of interest (ROI)
(c) Cropping biggest square contour
(d) Applying GCN and Morphological Transformation on extracted ROI
(e) Resizing all images to224 x 224 pixels

Fig. 2. Image preprocessing Results

and generate synthetic data with GANs to overcome the above challenges [14]. Fig. 3 shows the proposed GAN Architecture.

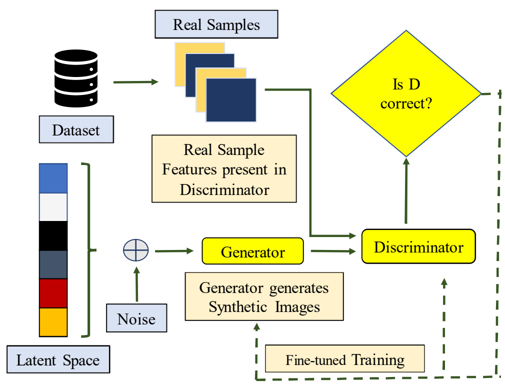


Fig. 3. GAN Architecture to generate Synthetic images of skin lesions.

For training the generative adversarial networks (GANs), we used the pre-processed training set images. GANs are designed with two parts they are: Generator (G) and Discriminator (D). Both of these structures are nothing but CNNs, and they compete with each other in an adversarial way. After training for few epochs, GANs can generate synthetic samples that are similar/identical to the original data. They have great potential as they can generate new identical images and can be trained to emulate any data patterns or distributions. Z is the input to G, which is a random noise vector generally picked from a Gaussian distribution. Using this input G generates an image, and the D tries to classify or distinguish if the output image from the G is original (real image) or fake (generated image). Upon training, G learns to mimic the original data and generate images close to real images, thereby fooling the discriminator. G learns by inspecting and analyzing every step and updating its parameters. Below is the mathematical expression (equation 1) showing the relation between G and D,

$$G = \min_{G}\max_{D}[\mathbb{E}_{x\sim\mathbb{P}_r}[log(D(x))]+\mathbb{E}_{\tilde{x}\sim\mathbb{P}_g}[log(1-D(\tilde{x}))]]. \tag{1}$$

However, due to frequent mode collapses and often failing to converge, training basic GAN is challenging. Many different approaches have been attempted to overcome these challenges. In this paper, we use the Wasserstein GAN with gradient penalty to generate synthetic data. This special GAN uses gradient penalty instead of weight clipping which was used in the prior version of WGAN to impose on the Lipschitz constraint, which is defined as a function $f(t, y)$ satisfy 1-Lipschitz constraint for variable y on a set D $\in$R^2 if there exists L such that $L > 0$ where L is Lipschitz constant. Equation 2 depicts the above relation:

$$L = |f(t, y_1) - f(t, y_2)| \leq L|y_1 - y_2|. \tag{2}$$

Additionally, the use of gradient penalty simulates the Lipschitz function more tightly, therefore ensuring the accurate calculation of Wasserstein distance. The new equation (equation 3) with gradient penalty showing the relation between generator (G) and discriminator (D) is depicted below

$$L = \mathbb{E}_{\tilde{x}\sim\mathbb{P}_g} log(D(\sim x)) - \mathbb{E}_{x\sim\mathbb{P}_r} log(D(x)) + \lambda E_{x\sim\mathbb{P}_r}[\nabla_{\hat{x}}||(D(\hat{x})||_2 - 1)^2]. \tag{3}$$

In our approach, we constructed both Critic and Generator with five convolution layers with activation function as Leaky ReLU with a negative slope of 0.2, including six Convolution Transpose blocks and Leaky ReLU activation function of critic and batch and normalization respectively. We have resized the training set to $224 \times 224 \times 3$ and fed it to the network for training. The optimizer used here is Adam with a learning rate, α = 10^{-4}, value of β = (0, 0.9) and the value of n_{critic} = 5. A total of 27,055 new synthetic images were generated of dimensions $224 \times 224 \times 3$ and were added to the original dataset. Table II depicts the metadata of the augmented dataset.

TABLE II
DATASET DESCRIPTION

Lesion Type	Original Data	Train	Test	(Train+Augmented) Data
Melanocytic Nevi	6705	5822	883	5822
Melanoma	1113	1067	88	5355
Benign Keratosis	1099	1011	46	5055
Basal Cell Carcinoma	514	479	35	4790
Actinic Keratosis	327	297	30	4455
Vascular Lesions	142	129	13	5160
Dermatofibroma	115	107	8	5350
Total	10015	8912	1098	35967

A total of 27,055 new synthetic images were generated of dimensions 224×224×3 and were added to the original dataset. Let I_{train}, $I_{validation}$ denote the training and validation sets of the image data before the training of the GAN. I_{gen} denotes the data generated by the GAN. We now split I_{gen} into 2 sets: $I_{genTest}$ and $I_{genTrain}$. The new training and validation sets are denoted by equation 4:

$$[I_{train}, I_{test}] = [I_{train} + I_{genTrain}], [I_{test} + I_{genTest}] \tag{4}$$

The below Fig. 4 shows a sample of the synthetic data generated by the W-GAN depicting each different lesion class. Fig. 4a shows a sample of synthetic data generated for the class Actinic Keratosis. Similarly, Figures 4b, 4c and 4d show the samples of the synthetic data generated for the classes Melanoma, Melanocytic Nevi and Vascular Lesions respectively.

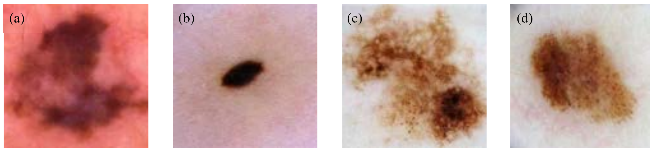


Fig. 4. Sample of Synthetic Data generated by W-GAN: (a) Actinic Keratosis, (b) Melanoma, (c) Melanocytic Nevi, (d) Vascular Lesions

D. Training CNN model

The primary goal is to train a deep learning model that can detect and classify different classes of skin lesions with high accuracy and generalization. Here, we use a CNN model. The main advantage of using CNNs is its potential to learn and extract the best and relevant features for better image classification. The following is represented in equation 5:

$$G[m,n] = (f*h)[m,n] = \sum_j \sum_k h[j,k]f[m-j,n-k]. \quad (5)$$

The input image is represented as f, and h represents the filter or kernel in the equation as defined above. Here m and n represent the indexes of rows and columns of the result matrix, respectively. A CNN architecture is used, which acts as a checkpoint for training the skin lesion prediction model. Many pre-trained CNN architectures are available, such as DenseNet-121, ResNet-50, VGG-16, AlexNet, etc. Here, we use Transfer Learning with different CNN architectures; using this is advantageous as it significantly reduces the training time and gives us better performance even with smaller datasets. Therefore, we us CNN architectures with Imagenet weights. Using the existing model as a base on top of dense layers is advantageous as it boosts learning by adding to the existing knowledge, thus giving better classification results. The image classifier is trained on top of base models to find the best architecture with the best performance. Out of the above architectures, DenseNet-121 has achieved the maximum accuracy of 92.2%.

E. Tensorflow Serving

The trained weights generated after training the model are saved using the .save function of Pytorch. To develop a robust prototype, the most efficient procedure is to convert the .pth file extension into a .pb file extension. To achieve this conversion, we use ONNX, which can convert a .pth file to a .pb file. Finally, using the TensorFlow Serving, we can create an app by embedding the trained TensorFlow model.

IV. Results and Experimental Analysis

The following section emphasizes on testing the performance of the SkinAid application along with the hardware specifications used for training SkinAid.

A. Hardware specifications of the SkinAid App

The SkinAid app was tested on the conditions of 4GB RAM, 12GB free internal memory and 48MP android camera. The minimum conditions for the efficient performance of SkinAid are 2.5GB RAM, 150Mb storage and 8MP android camera. Table III shows the hardware specifications of the SkinAid app.

TABLE III
Hardware specifications of SkinAid

Hardware specification	Testing Conditions	Minimum Conditions
RAM	4GB	2.5GB
Internal Memory	12GB	150MB
Camera	48MP	8MP
Internet Connectivity	50Mbps	Nil

B. User Interface and Android Application Results

This application is used as a tool for dermatologists to identify the lesion's nature. The user (dermatologist) first identifies the lesion on his body and subsequently uses the android camera to capture the lesion and stores it in the edge device. Then the user opens up the SkinAid application and identifies the visible symptoms. This is called the symptom analysis step. In the next step, the user uploads the lesion image and obtains the class of the lesion. Figure 5 shows the presence of the lesion on the skin of the user and its successive magnification. Similarly, Fig. 6 shows the deployment results of SkinAid.

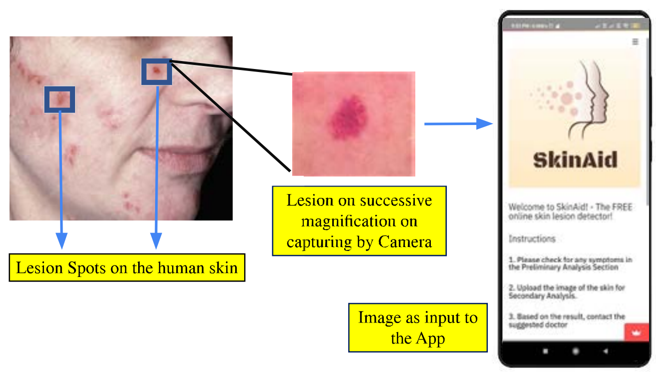


Fig. 5. User Input on SkinAid Interface

C. Performance comparison of different CNN Architectures

The different architectures are firstly trained on the original dataset and their accuracy is recorded. They are then trained upon the augmented dataset involving both the conditions of non pre-processed images and pre-processed images and their accuracy is obtained. From Table IV, we can infer that DenseNet-121 has the highest accuracy amounting to 92.2%.

D. Precision, Recall and F1-Score

From Table. IV, we can infer that the number of Images of the class "Melanocytic Nevi" are greater in number than the other classes. This implies that the W-GAN had a bigger latent space as compared to the other classes. To be precise, the GAN had more features to train on. As a result, the Precision, Recall and F1-Scores of the class Melanocytic Nevi are greater than

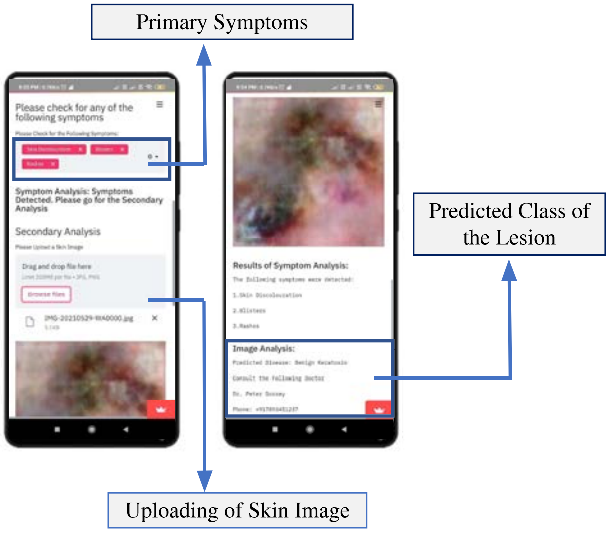


Fig. 6. Detection and Classification of Skin Lesion

TABLE IV
ACCURACIES (IN %) FOR VARIOUS DEEP LEARNING MODELS

Sl.No	Classifier Networks	Accuracy (%)		
		Original Dataset	Augmented Dataset	
			No Preprocessing	Preprocessed
1	VGG-16	63.3	70.5	83.7
2	ResNet-50	68.1	71.9	87.3
3	ResNet-101	68.7	71.3	87.8
4	MobileNet-v2	66.4	69.8	89.6
5	Inception-v3	69.2	73.1	90.8
6	DenseNet-121	70.4	73.0	92.2

the other classes. Similarly, as the number of images of Actinic Keratosis class were less in number, it had a lesser F1-score. Table V depicts the precision, recall and F1-Score values of DenseNet-121:

TABLE V
PRECISION, RECALL AND F1-SCORE OF DENSENET-121

Class	Precision	Recall	F1-Score
Actinic Keratosis	0.75	0.73	0.739
Basil Cell Carcinoma	0.75	0.80	0.774
Melanoma	0.85	0.73	0.785
Dermatofibroma	0.85	0.75	0.796
Melanocytic Nevi	0.94	0.96	0.949
Vascular Lesions	0.83	0.76	0.792
Benign Keratosis	0.78	0.71	0.743

V. CONCLUSIONS AND FUTURE WORK

In this paper, a smartphone aided IoMT framework for skin lesion detection and classification was formulated using GANs and deep CNNs. The app has been put into meticulous testing on various skin lesions belonging to the seven different classes and has obtained good results on them. The SkinAid app can be used by any healthcare professional across the globe without the interference of internet to obtain preliminary analysis and classification. It empowers the rural health centres by detecting potential lesions in an early phase, thus reducing the cost of treatment and providing awareness about skin cancers.

In the subsequent aspects of the proposed solution, the SkinAid application can be improved to detect more classes of skin lesions with improved accuracy and efficient image data. Security and privacy issues in the Smart Health also needs research within the given constraints.

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