Skin Disease Detection Prediction Using Convolution Neural Networks

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***Abstract*— The body's largest organ, skin, is not only a fantastic shield for precious organs, but it also provides numerous functions. It serves the purpose of a coating that guards against our internal organs from getting damaged. Moreover, it is interesting to note that the respiratory system, one of the very significant parts of the human body, can be interfered with, with some serious infection caused by fungi or viruses or dust too. Nowadays lots of people have different requirements concerning their bodies than in the past and many of us are able to afford choosing and changing them. In the world there are millions of people that have lots of different skin diseases. With an ecstasy of acne and eczema people are in great pain. Sometimes, a small pimple familiar to the human skin becomes a serious problem that might even turn into full-scale infections. Some of the skin gems, if not contagious, can be contracted, say while shaking hands with another person or using another person's handkerchief. Ensuring an accurate diagnosis, a person in the suffering who diagnosed is provided with medication that can limit the miseries the individual goes through. Our research is oriented to train neural network to provide diagnosis of skin ailments using a developed prototype. We have chosen CNN which abbreviates UKN for Convolutional neural network. The method of detecting activities earlier is already done by using DNN; a deep neural network. As of now, we have some classes for common hand diseases, manner this is dermatitis hand, eczema hand, eczema subcute, lichen simplex,statis dermatitis or ulcer. and their application are the two sides which hold together the sandwich between them. Having been developing the picture which has been reported by CNN via planning, when organizing education. The preparation information is made up of five units regarding one of which is the human skin that has been discussed in the beginning.**

I. INTRODUCTION

Skin is inherent of our body, the part of us that is most difficult to detach. It is responsible for the provision of a protective barrier to our kidney, heart, liver and other organs that are very delicate and sensitive to the outside environment. It is this body segment that acts on defense and only with its status, we can have a healthy lifestyle. Tee or epidermis plays key role in producing necessary vitamins crucial one among them is vitamin-D. If these cells are infected, then problem will increase number of nuies.

https://github.com/Chandana1013/DL-Final-Project/
https://github.com/HemanthLakkimsetti76/DL-Project
https://github.com/Chandana9829/FINAL_PROJECT
https://github.com/JGayathri3/DL-Final-Project-Increment

Around the globe, in different climates, some places are hot and humid, other places are cold, and the inhabitants of different places eat their native foods, with all of the variations, either directly or indirectly skin can be affected. We solve any problem that is measured with numbers, science, or economics, by going ahead and finding out the problem we want to solve. One of the first things to do before making any treatments to our skin is identifying the specific disease. The skin is the most affected by fungus as well as different kinds of infections that can be caused by them. Suffering from skin problem is a common fact in everyday life because we spend too much time outdoor under the sun where sweat full of bacteria and in the pollution which cause do to the moisture which is a house of bacteria that creates bad smell and it also causes some skin problems. The skin's stomping out the infection as hygiene is the most powerful punch to skin issues. However, some conditions develop to the point that they are urgent and require prompt vaccination. Direct business is our main means. We were able to establish a record for CNN over an image processing so that we can introduce a medicine development in the medical field which we refer to as Derm-NN. It is a pattern recognition algorithm using deep learning architecture from a well-known convolutional neural network to identify the skin diseases. In our research work, we have made a prototype classifier which provides a class of skin disease by analyzing an image and comparing the image with the earlier existing data and classify with highest accuracy.

And in this task, we applied dermnet images dataset, some of which are caught from the internet randomly. Our classifier can indeed achieve the 70% accuracy for skin condition identification. As for the skin complaints we propose 5 categories. The diagnosed part of our dataset played a training phase as well as testing phase. This is the situation where the person is normally not okay and some organs of the body certainly stops its normal functions due to some content in the body like the blood sugar level for example. Pemphigus is a condition when the immune system begins to attack the own skin due to a bacterium that accelerates the body to produce red and itching skin, blisters and so on. The fact that the convolutional neural network is have been demonstrated to have and can share in field of computer vision and machine learning is yet an evidence of the capabilities of the technology. It constitutes a type of neural network. # It has demonstrated its efficiency by dealing with the end of image processing as well. In the process, the computer undertakes the task of visual classification which is called “Imaginary Classifier.” We have built this classifier that will take images that have been polluted skin and the learned knowledge in training data and it shall classify the dataset accordingly. Data they ascent and data they obtain as a result has been given in different parts of this paper. Eczema is not an issue that captures attention nowadays. With the reason for this to get awareness about the issue, we encourage its activation. In addition to long or short term, their value of interest on the skin may cause harm. With a doctor wearing the digital technology known as google glass, the digital era has even reached such heights of medics that it is scanning patients. Do the same treatment in the area of dermatology also. In the proposed instant, we will design a system isometric graph that will be linked with the image processing techniques to help the patient get specific data about their skin using their cell phone or personal computer program.

Our guideline for this paper is to provide the patients with rapid aid so then they can meet up to their requirement. It is worthwhile to note that some terms and conditions are applicable. against the elimination of diseases as a potential source of gain for it. At the first step, they will take a picture of the contaminated area of the skin and send the image to our app, which is then uploaded to the central server. Our app will process the images of illness in the central server, and it will answer with the name of the skin problem taken as an example, if there are 5 diseases that were trained on [3]. Convolutional neural networks (CNN) have been applied in this study to identify five skin diseases: Dermatitis hand eczema, etcial simplex, Stasis dermatitis, and childhood ulcers. Through this gap, this autogenous system can recognize the diseases and give support based on the image analysis report, which leads to the solution of this problem.

This paper has been broken into six pieces for your convenience. In Section I, we provide an overview of the subject matter. Section II provides an overview of the research methodology. A further discussion of deep learning-based classifiers, their performances, and datasets was also included in this section. Section III contains the results. Section IV presents a summary of our findings and conclusions from our research. The topic of future work is also included in this section. The Acknowledgement section is found in Section V.

II. Related Works

The emergence of hybrid technology with medicine catalyzes process acceleration in imaging processing for medical usage to support the medical industry. Acquisition of digital image-enhanced technologies like Computed Tomography (CT), Digital Subtraction Angiography (DSA), and Magnetic Resonance Imaging (MRI) is definitely collecting accurate diagnosis. Dermal diagnoses have brought rashes into the arena of researchers for a long time. As such the attached PowerPoint presentation includes, among others, a literature tab.

Ercal et al. [1] presented an adaptify color metric based on primary red, green, and blue planes. Not only is it useful for the border of the tumor area and the background separation but also in the tumor region differentiation. Image segmentation is the process by using some suitable coordinate transformation. Borders are depicting a region of interest drawn around the tumor segmented from the image. This proved as an excellent technique for the purpose of directing guidance and treatment of a cancerous organ.

The method of S. Pari et al., [2] was utilizing the deep convolutional neural networks, image classification algorithms with data augmentation that had been used successfully to perform automatic detection of dermoscopic patterns and skin lesion analysis. Using this system, Ganster and his co-authors [3] managed to instantly evaluate ELM images measured by a computer. Skin mask segmentation into non-lesion and lesion classes are done by using diverse basic algorithms with integration strategy. Cancerfinity of the tumor is rated by morphologic and radiodiagnostic characteristics. The objective is to capture a balance between the local and the global factors is also an important aspect. The machine learning system increases the chance of early diagnosis of malignant melanoma.

Grana et al. [4] developed a model approach that is mathematical in nature to check the lesion border. The process would involve a determination of luminance value in relation to the normal direction of the line at each point. Emphasizing specific data point with the help of reference [5]. Sigurdsson et al. [5] classified skin cancer by applying in vitro Raman spectroscopy. They employed a nonlinear neural network classifier to perform the lines of work. One of the most unique features is that different percentages of lipids and proteins causes the notable absorption bands visible in this spectrum. As a result, this helps to classify and detect different types of skin lesions.

Aberg with all the co-authors [6] uses electrical bioimpedance to measure the skin cancers and lesions status. The significant difference in multi-frequency impedance spectra exists between malignant melanoma and benign nevi for skin cancer; however, this is not the case with nevi and benign tumors. The authors of the paper Wong et al. [7] introduced an adaptive stochastic region merging method to distinct lesion regions from the macroscopic images. This is in the process where initially, stochastic merging regions is executed on pixels level, then merge region until convergence.

In the study by Wighton et al., [8] a well-implemented automated skin lesion diagnosis was the top priority. An approach based on supervised learning and MAP estimates is proposed for the diagnosation. The researchers [9] take advantage of ensemble thresholds to border lesion detailing on dermoscopy photos.

Oyola and Arroyo [10] take into account classifying a varicella image by means of Hough transforms, and they are applying the processes of image processing like color transformations, equalization and edge detection. It assists in detection of varicella with improved precision and outcomes.

III. METHODOLOGY

A. Datasets

This dataset contains the training data for the ISIC 2019 challenge, notice that it already includes data from prior years (2018 and 2017). The dataset for ISIC 2019 contains 25,331 photos that may be classified into nine different diagnostic groups based on their dermoscopic appearance.

- Melanoma
- Melanocytic nevus
- Basal cell carcinoma
- Actinic keratosis
- Benign keratosis (solar lentigo / seborrheic keratosis / lichen planus-like keratosis)
- Dermatofibroma
- Vascular lesion
- Squamous cell carcinoma
- None of the above

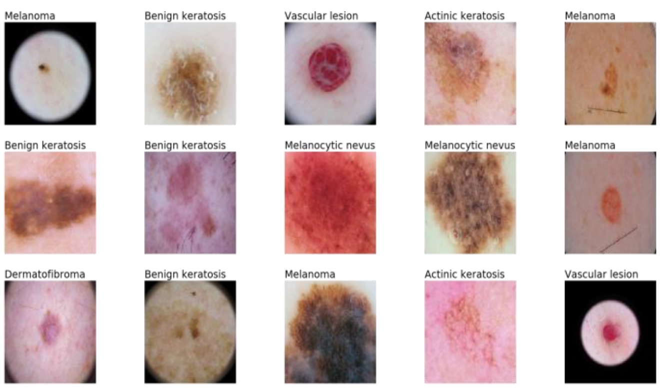

Fig 2. Dataset Sample

B. Data Preparation

In data preparation, we transform raw data into a more suitable form to create an effective model. There are some factors in data preparation such as data cleaning, feature selection, data transforms, feature engineering, dimensionality reduction, etc that finalize the dataset for training.

Preprocessing

Data preprocessing is the first and crucial step in preparing the raw data and making it compatible with a machine learning model. The main objective of preprocessing our dataset is to enhance the original medical images by removing air bubbles, noise, and artifacts which are caused by applied gel before capturing images.

Data reduction

In imaging dataset, data reduction is the process of reducing the number of images from the original data into a smaller volume. It is a great challenge to get the best classification rate from the overall dataset due to having many images with noise and artifacts, some blur images, some images that have low contrast, some images that have mole beside the wounds, and some images have color illumination

Normalization of data

Data normalization is the way toward planning the database that diminishes data redundancy, data uprightness, and takes out unfortunate characteristics like insertion, update, and deletion anomalies. There are a few existing techniques of normalization such as min–max normalization, z-score normalization, and decimal scaling normalization

Feature extraction

Feature extraction is a technique that plays a vital role in image processing to make it more manageable for further processing. In our research, we extract a huge amount of features that helps to identify and recognize the pattern of a large number of dataset

Data augmentation

Data augmentation is a strategy that is used for artificially increasing the amount of data by adding slightly modified copies without actually collecting new data from existing training data.

Transfer learning

Transfer learning is a machine learning technique in where the pre-trained model can be reused on different but related problems. It is a challenging task to train a large size of medical datasets like ImageNet using all the parameters that exist in the neural networks. So we are using AlexNet and Adam optimizer is used as a gradient descent algorithm.

C. Modeling

I. AlexNet

The AlexNet consists of eight layers with weights; the first five of these layers are convolutional, while the latter three layers are completely connected. This distribution is produced by feeding the output of the last fully-connected layer into a 1000-way softmax, which provides a distribution over the 1000 class labels Multinomial logistic regression is the aim that the network seeks to maximize, which is similar to maximizing the average over training cases of the log-probability of the right label under the prediction distribution. Convolutional layers 2, 4, and 5 are connected exclusively to kernel maps in the preceding layer that are located on the same GPU as the second, fourth, and fifth convolutional layers, respectively. It is possible to connect the kernels of the third convolutional layer to all of the kernel maps in the second layer. In fully-connected layers, all neurons in the previous layer are coupled to all neurons in the layer above them.

AlexNet consists of five convolutional layers and three fully linked layers, to summarize. Relu is applied after a layer that is highly convolutional and fully linked. Dropout is implemented prior to the first and second years of being completely linked to the internet. The network comprises 62.3 million parameters and requires 1.1 billion compute units in a single forward pass, according to the network's specifications. We can also observe that convolution layers, which account for only 6% of all the parameters yet cost 95% of the work, are utilized.

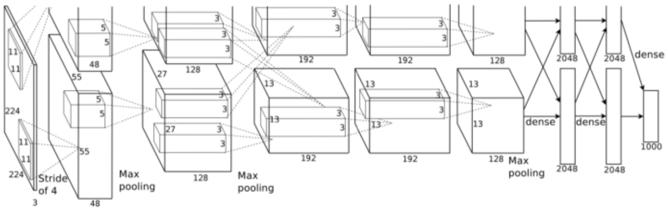

Fig 7. AlexNet Architecture

- It has 8 layers with learnable parameters.
- The input to the Model is RGB images.
- It has 5 convolution layers with a combination of max-pooling layers.
- Then it has 3 fully connected layers.
- The activation function used in all layers is Relu.
- It used two Dropout layers.
- The activation function used in the output layer is Softmax.
- The total number of parameters in this architecture is 62.3 million.

II. DenseNet

DenseNet is an architecture that focuses on making deep learning networks go even deeper while also making them more efficient to train because it uses shorter connections between the layers. Specifically, DenseNet is a convolutional neural network in which each layer is connected to all other layers that are deeper in the network; for example, the first layer connects all other layers that are deeper in the network, and the second layer connects all other layers that are deeper in the network, and so on. This is done in order to ensure that the most amount of information can flow between the layers of the network. In order to maintain the feed-forward nature of the system, each layer obtains inputs from all of the previous layers and passes on its own feature maps to all of the layers that will come after it.

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112 × 112	7 × 7 conv, stride 2			
Pooling	56 × 56	3 × 3 max pool, stride 2			
Dense Block (1)	56 × 56	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6
Transition Layer (1)	56 × 56	1 × 1 conv			
	28 × 28	2 × 2 average pool, stride 2			
Dense Block (2)	28 × 28	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12
Transition Layer (2)	28 × 28	1 × 1 conv			
	14 × 14	2 × 2 average pool, stride 2			
Dense Block (3)	14 × 14	[1 × 1 conv, 3 × 3 conv] × 24	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 48	[1 × 1 conv, 3 × 3 conv] × 64
Transition Layer (3)	14 × 14	1 × 1 conv			
	7 × 7	2 × 2 average pool, stride 2			
Dense Block (4)	7 × 7	[1 × 1 conv, 3 × 3 conv] × 16	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 48
Classification Layer	1 × 1	7 × 7 global average pool			
		1000D fully-connected, softmax			

Fig 7a.various architectures of DenseNets

In contrast to Resnets, it does not combine features by summarizing them; instead, it concatenates the features to form a new feature. As a result, the 'ith' layer has I inputs and is composed of feature maps from all of the convolutional blocks that came before it. Those feature maps that it generates are passed on to all of the subsequent 'I-i' layers. In contrast to traditional deep learning architectures, this introduces '(I(I+1))/2' connections into the network, rather than just 'I' connections as in previous architectures.

$$\mathbf{x}_\ell = H_\ell(\mathbf{x}_{\ell-1}) + \mathbf{x}_{\ell-1}.$$

Thus, it requires fewer parameters than traditional convolutional neural networks because there is no need to learn unimportant feature maps, as there is with traditional convolutional neural networks.

$$\mathbf{x}_\ell = H_\ell([\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_{\ell-1}]),$$

Aside from the fundamental convolutional and pooling layers, DenseNet comprises two important building blocks. The Dense Blocks and the Transition layers are the two types of layers.

DenseNet begins with a simple convolution and pooling layer that serves as a foundation. Afterward, there is a dense block followed by a transition layer, another dense block followed by a transition layer, yet another dense block followed by a transition layer, and finally a dense block followed by a classification layer, which is the final step.

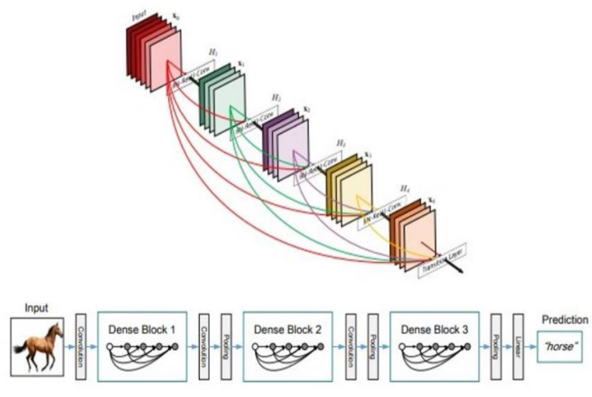

Fig 7b. Various blocks and layers in DenseNet

Specifically, DenseNet is a convolutional neural network in which each layer is connected to all other layers that are deeper in the network; for example, the first layer connects all other layers that are deeper in the network, and the second layer connects all other layers that are deeper in the network, and so forth. In Using Standard ConvNet, the input image is convolutioned multiple times to obtain high-level characteristics. As each layer of the DenseNet architecture receives additional input data from all preceding layers, it sends its own feature maps to the subsequent layers. Concatenation is used in this case. Each layer is receiving "collective knowledge" from all of the layers that came before it. Because each layer receives feature maps from all preceding layers, the network can be made thinner and more compact, resulting in a smaller number of channels. The growth rate k is the number of additional channels that are added to each layer. The following steps are performed for each composition layer: Pre-Activation Batch Norm (BN) and ReLU, then 3-3 Conv with output feature maps of k channels, for example, to transform x0, x1, x2, x3, and x4 to x4.

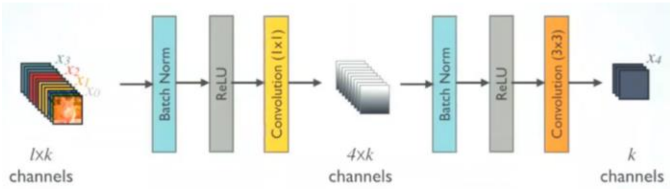

Fig 8: Steps Performed in DenseNet composition layer

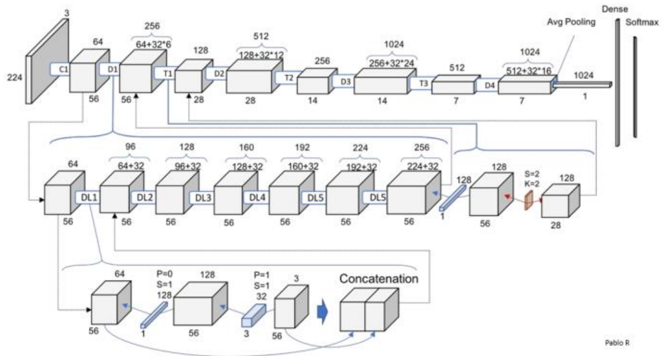

Fig 8a. Full architecture of DenseNet

The number of filters changes between the DenseBlocks, increasing the dimensions of the channel. The growth rate (k) helps in generalizing the lth layer. It controls the amount of information to be added to each layer.

$$k^{[l]} = \left(k^{[0]} + k(l-1) \right)$$

D. Validation Method

In classification When we say "accuracy," we are usually referring to the degree to which something is accurate. It is one of the more visible metrics because it is the total number of cases that have been accurately detected. When all of the classes are equally essential, this is the most frequently encountered situation.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{(\text{True Positive} + \text{False Positive} + \text{True Negative} + \text{False Negative})}$$

Precision: It is implied as a measure of the proportion of successfully detected positive cases among all of the expected positive instances. As a result, it is advantageous when the costs of False Positives are substantial.

$$\text{Precision} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Positive})} = \frac{25}{(25+5)} = \frac{25}{30} = 0.83$$

IV. RESULTS

The AlexNet model has achieved 65% of accuracy in classifying the lesion melanoma. It seems like the model has a problem of overfitting. We have to reduce the overfitting by adding dropouts. The DenseNet model has achieved 93% of accuracy in classifying the lesion melanoma. With the help of dropouts the. Model can overcome the overfitting issues.

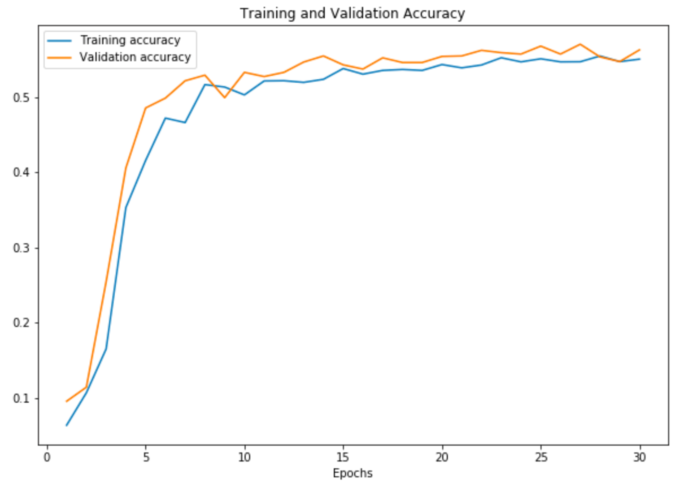

Fig 9a. AlexNet method Accuracy

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Label : AK
Skin Lesion Name : Actinic keratosis
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Fig 9b. AlexNet method Result

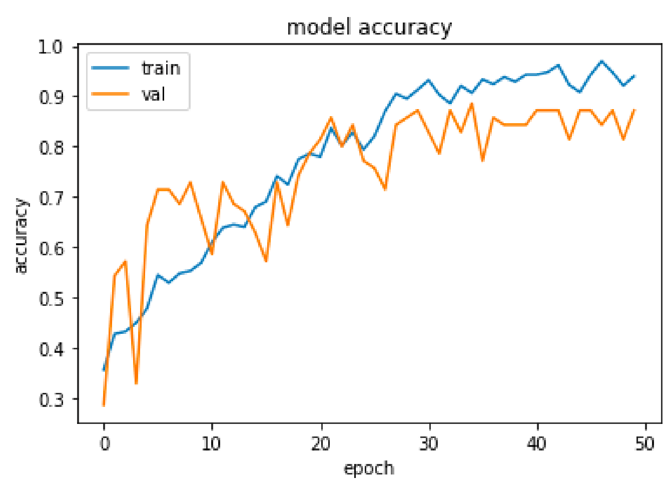

Fig 9c. DenseNet model accuracy

Fig 9d. DenseNet model Result

V. CONCLUSION AND FUTURE WORK

The skin disease pictures shot with a digital camera got caught, the processing of which was done with these images. Picture handling is a strategy that can be partitioned into various classes: the other two techniques are Image Compression together with image keying and recycling, respectively. We hope that our model will be proven as a practical thing helping our clinical science to bring relief to the government of patients. Identification of the ailments for the developed states will be an add-on for they can now focus on setting their priorities for the gain of their future healthy skin. This study analyzed the in-depth technique of DenseNet which is a pretrained CNN based model. It has been observed that using deep learning technique DenseNet, there has no dire need for complex and composite pre-processing techniques such as image resize, crop and pixel value normalization. The DenseNet method showed better results than the other conventional deep learning methods. With this method we have achieved 93% of accuracy which can easily classify the skin lesion. In future, the method has to be modified a bit more complicated to get more accuracy. Also, we can change the optimizer.

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