

Developments in Deep Learning for the Diagnosis of Skin Cancer

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DOI: <https://doi.org/10.51583/IJLTEMAS.2025.1406000101>

Received: 05 July 2025; Accepted: 07 July 2025; Published: 22 July 2025

Abstract- The most prevalent kind of cancer worldwide is skin cancer. Early detection is crucial since failure to discover it in the primary stage could be fatal. Even though there are distinctions within the class and a lot of parallels between classes, it is too hard to tell with the naked eye. Due of the disease's widespread occurrence, several automated deep learning-based algorithms have been developed to date to assist physicians in spotting skin lesions early on. We trained VGG19 on the HAM10000 dataset by fine-tuning the Convolutional Neural Networks (CNNs) and using pre-trained ImageNet weights. With FT, the best performance was noted. With an overall accuracy of 82.4 ± 1.9 percent, the developed model outperformed the one employed in transfer learning. This performance could save morbidity and treatment costs by providing a second opinion and bolstering the clinician's diagnosis.

Keywords- Convolutional Neural Network, dermatology, deep learning, transfer learning, fine-tuning, image classification, medical imaging, skin cancer, and artificial intelligence in healthcare

I. Introduction

The uncontrolled growth of skin cells, which is mostly brought on by genetic defects or DNA mutations, is a pathological state known as skin cancer. Long-term exposure to UV light from the sun is the main cause of this abnormality [1]. Additional factors that raise the risk of developing skin cancer include drinking alcohol, being overweight, getting sunburned, being exposed to radiation, having a family history of the condition, having weakened immune systems, and having genetic abnormalities [2-4]. In certain medical picture applications, DL techniques—in particular, Convolutional CNNs—have become the favored paradigm. Before sending them to fully connected neural networks, deep convolutional neural networks (DCNNs) have been shown to effectively integrate low-, middle-, and high-level characteristics across the network [7, 8]. Rather than using a variety of intricate models, T. Emara et al. (2019) have suggested a single, modified Inception-v4 model for the classification of data that has been taken from the dataset. More precisely, by employing feature reuse, the efficiency of the suggested model was increased by include long residual connections.

This involved combining high-level layers with previously collected features from the earlier layers, which enhanced the model's classification performance. The correctness of the suggested architecture, when evaluated on a testing set, was 94.70% [2]. Z. Qin et al. (2020) have enhanced the proven skin lesion classification performance by the use of a data augmentation technique based on Generative Adversarial Networks (GANs).

The suggestion for skin lesion style-based GAN types adhered to the fundamental style-based GAN model. The classifier for picture categorization was constructed using a transfer learning technique on top of a deep neural network that has already been trained. In order to

help train the classifier for better classification performance, the training set was eventually extended to incorporate synthetic images from suggested skin lesion style-based GANs. Following the addition of synthesized images to the training dataset, the main classification indicators—sensitivity, accuracy, specificity, balanced multiclass accuracy, and average precision—were 83.20%, 95.2%, 74.30%, 83.10%, and 96.60% on the International Skin Imaging Collaboration (ISIC) 2018 Challenge [9].

A. Mahbod et al. (2020) investigated the effects of image size on skin lesion categorization using pre-trained CNN and Transfer Learning (TL) techniques. The dermoscopic pictures taken from the ISIC skin lesion classification challenge data-sets had undergone scaling and cropping processes. This resulted in six different sizes, ranging from 450×450 to 224×224 . Three widely used CNNs—EfficientNet-B1, EfficientNet-B0, and SeReNeXt50—have had their classification efficiency examined. Additionally, they evaluated a fusion strategy known as the multi-scale multi-CNN (MSM-CNN) and published a proposal.

The method used in this work is based on a three-leveled ensemble strategy that makes use of three different network architectures. Such a design has been trained using cropped dermoscopic images of varying sizes. Their study's findings indicate that, in contrast to image resizing, When used as a strategy, image cropping improved categorization performance. Every image scale that has been examined has seen this benefit. The MSM-CNN method demonstrated balanced multi-class accuracy on the ISIC 2018 skin lesion categorization challenge test set [10].

A state-of-the-art deep convolutional neural network (DCNN) model was introduced by M. S. Ali et al. (2021) and demonstrated remarkable effectiveness in accurately classifying benign and malignant skin lesions. During the pre-processing stage, the researchers first used a kernel or filter to eliminate noise and artifacts from the input images. They then proceeded to identify the

important features that aid in precise data classification and normalize the input photos.

Lastly, by employing data augmentation techniques, the researchers have expanded the number of images, improving the classification rate's accuracy. To assess their suggested DCNN model, the researchers performed comparison analysis utilizing a number of TL models, including ResNet, MobileNet, VGG-16, AlexNet, DenseNet, and others. For training and testing accuracies, Maximak reported values of 93.16% and 91.93%, respectively [11]. A DCNN model comprising many layers and different filter sizes was developed by I. Iqbal et al. in 2021. It has been improved to contain fewer filters and parameters in order to improve performance and efficiency.

Dermoscopic images have been created by experiments using (ISIC-18, -17, and -19) data. A few parameters, including sensitivity, specificity, accuracy, and others, have been used to show the experimental outcomes of the proposed DCNN technique. The model has demonstrated 94% accuracy, 93% sensitivity, and 91% specificity with regard to the ISIC-17 dataset. The suggested DCNN technique outperformed the existing algorithms, according to experimental results. In particular, it assigned an area under the receiver operating characteristics of 0.964 to the skin lesions in the ISIC17 [12]. CNN architecture, notably MASK R-CNN, was proposed by M. A. Khan et al. (2021). The Resnet50 model and the feature pyramid network (FPN) supplied the foundational architecture.

Building the final mask required the mapping of features based on completely connected layers. A CNN architecture consisting of 24 layers was developed during the classification phase. In this type of architecture, activation mechanisms rely on higher-level features manifesting. The best CNN features were ultimately used and integrated into soft max classifiers to carry out the final classification. The segmentation approach was validated using three datasets: PH2, ISBI2016, and ISIC2017. In contrast, the HAM10000 dataset was used for the categorization. The previously given characteristics, which include F1-Score 86.28%, precision 87.01%, sensitivity 85.57%, and 020401-02 accuracy 86.5%, show that the suggested procedure outperforms existing tried-and-true approaches [13].

We propose a skin lesion classification system based on deep neural networks in the paper that is being presented. networks. There were seven different kinds of skin lesions in our dataset, HAM10000. We initially scaled the photos to match the input size of the training model. The issue of excessive data imbalance was resolved, which impacts the task of multi-class categorization. We gave that data at least one label to describe its context in order to allow the models to provide precise predictions. The input photos have been adjusted to fall inside a standard range of 0 to 1. To get around these problems, DL classification networks require a substantial amount of training data; we increased the training data. The models have been trained using various combinations of hyper-parameters to achieve the best results. The VGG19 model, which is trained using FT and TL, was used. Finally, the performance of the categorization models was evaluated using five criteria.

II. Methods

This section offers a thorough explanation of every tool and method we used to build the recommended system, including pre-trained models, data preparation, and model training.

VGG19

VGG19 is a variant of the VGG model that is based on the VGG16 design [14]. The main difference is the architecture's depth. It follows the same basic pattern of convolution and maxpool blocks as VGG16 despite having 19 layers: 3 fully connected layers, 16 convolution layers, 5 maxpool layers, and 1 softmax layer [15].

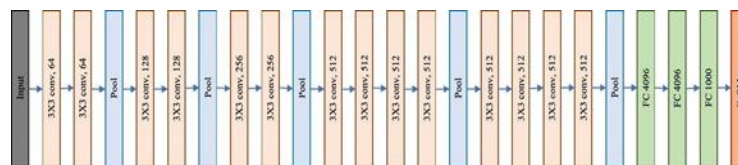


Fig 1. VGG19 Architecture [16]

Dataset

The HAM10000 ("Human Against Machine with 10015 images") dataset was used in this study. This dataset is also known as the ISIC 2018 dataset because it was made available via the ISIC 2018 classification competition. Table 1 lists each of the seven categories of skin lesions that are present in HAM.

Table 1. Dataset distribution

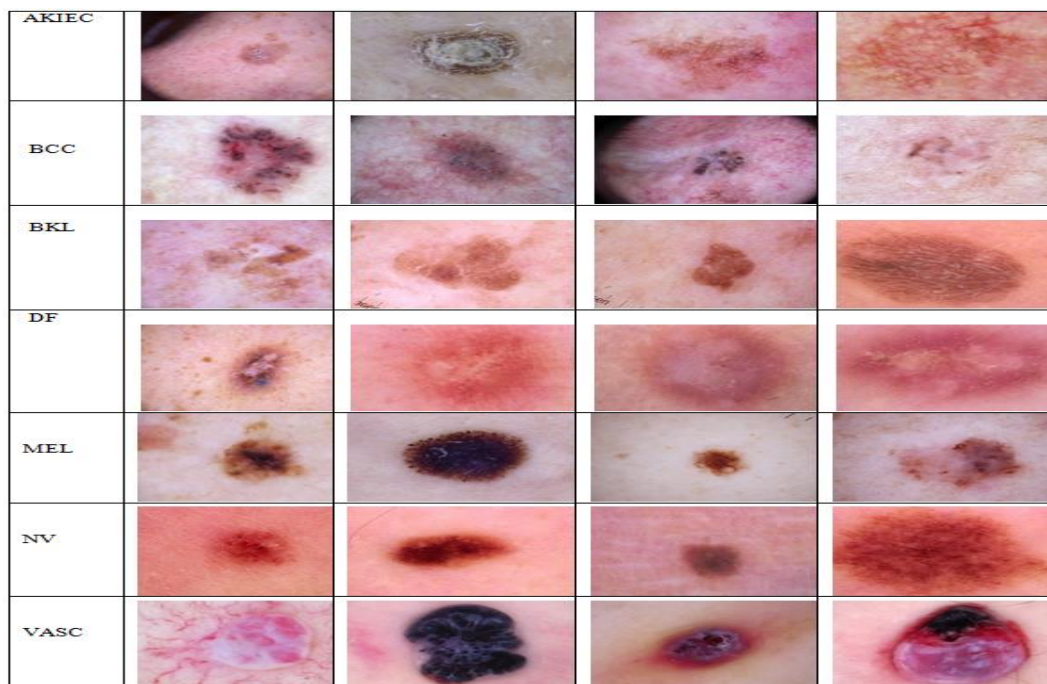
Diagnostic category	Symbol	No. of images	Ratio
Actinic Keratosisand Intraepithelial Carcinoma	AKIEC	327	3.27%
Basal Cell Carcinoma	BCC	514	5.13%

Benign Keratosis	BKL	1099	10.97%
Dermatofibroma	DF	115	1.15%
Melanoma	MEL	1113	11.11%
Melanocytic Nevi	NV	6705	66.95%
Vascular Lesion	VASC	142	1.42%

More than 95% of the different kinds of skin lesions are covered by those seven comprehensive diagnostic groups. While inter-class resemblance can be rather high, there are discernible variances within a single class. Furthermore, it is an uneven class dataset, with dermatofibroma accounting for only 1.15 percent of the photos and melanocytic nevi for nearly two thirds. In terms of image quality, the lighting and perspective in the photos vary. Because of this, differentiating between those seven classes might be a significant problem for the classifier. Figure 2 shows sample photos for each class. The Kaggle repository makes the dataset publicly accessible. [17]

Pre-processing

Data pre-processing has a major impact on skin disease diagnosis when employing DL. One of the procedures carried out in this study was image scaling, the most widely used pre-processing technique. Every image in the dataset was scaled from 450×600 RGB to 224×224 as required by the models. Data labeling, also known as data annotation, is a preprocessing phase in the model-creation process. To accomplish that, at least one label has been added to each class. Evidence of the high class imbalance in the final dataset is shown in Table 1, which will seriously skew the system's performance.



One of the data constraints influencing the performance of the DL model is data imbalance. In certain instances, there are significantly more training instances in one category than in another. The training is biased in favor of the majority, and the model has limited possibilities to learn about minority classes. This model consequently fails to appropriately handle data that belongs to the minority class and continues to identify all input as belonging to the majority class. 500 samples were created for each class in the data set in order to balance the data and address this issue. The original photos then undergo a normalizing process. The criterion that has been used to prevent issues during training is division 1 between the maximum pixel value, which yields values between 0 and 1 in the case of 1/255.

Data augmentation

To properly train DL classification networks, a substantial amount of training data is required. Augmentation procedures have been performed on the training set to increase the number of training images and avoid the overfitting issue that may occur when using insufficient training data in order to address such problems. Zoom, rotation, height shift, width shift, vertical flip, and horizontal flip were among the changes applied to the original training images in order to achieve this goal, creating new training samples for the training set. Images have been subjected to random rotations of up to 360 degrees. Furthermore, random zoom has been applied with a 0.20 factor; height and breadth shifts have also been applied with a 0.20 factor; and random flips have been carried out both horizontally and vertically.

Hyper-parameter tuning

Hyper-parameters like the number of layers, optimization technique, learning rate, and activation functions have a big impact on how well neural networks perform. Determining the hyperparameter is one of the most crucial issues that any researcher working in the field of neural network design must deal with because a poorly described set of parameters could lead to an underfitting or overfitting model. For this investigation, the VGG19 DL model was trained, and the hyper-parameter was set for the best possible setup. To get the right results, we trained several times with different hyper-parameter settings. After a number of tests, the model was optimized using the Adam technique. Adam's beta1 and beta2 values were 0.9 and 0.999, respectively. We used a learning rate of 0.001 and 100 epochs. The batch size for the model was 32.

$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall}$	(4)
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Evaluation criteria

Metrics like sensitivity (recall), accuracy, precision, and specificity are commonly used in classification algorithms to assess their effectiveness. The classification findings of certain samples are explained in detail by a confusion matrix. One part of the confusion matrix displays the comparison of the actual and expected labels for every image in the testing set. The number of cases for which accurate predictions were made is known as true positives, or TP. The number of cases that were mispredicted is known as false negatives (FN). The number of negative occurrences that were accurately predicted is known as true negatives (TN). The number of negative cases that were mispredicted is known as false positives (FP) [18, 19].

The performance of the categorization models was evaluated using five criteria:

Precision is defined as the ratio of accurately predicted positive samples to all anticipated positive samples [20].

$$precision = \frac{TP}{TP + FP} \quad (1)$$

Accuracy: Accuracy is defined as the ratio of all correctly predicted samples to all samples [20].

$$Accur = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

Recall: To measure the classifier's capacity to accurately identify positive samples, recall—also referred to as sensitivity—is the proportion of correctly categorized positive samples. Equation (3) provides the formula for expressing the recall. [21].

ROC: The receiver operating characteristic curve, or ROC curve for short, illustrates the relationship between a parameter's sensitivity (true positive rate) and specificity (false positive rate) at various thresholds. The area under the ROC curve, which varies from 0.1 to 1.0, is known as the area under the curve (AUC). AUC allows for a direct evaluation of the classifier's quality because it is a numerical metric. Classification accuracy rises with increasing AUC. The balance or imbalance of sample categories has no bearing on the AUC metric [23].

III. Results and Discussion

The usefulness of the proposed method for categorizing skin lesions is evaluated in this section. In particular, we categorize the lesions from the HAM10000 dataset and objectively assess performance using five conventional criteria in medical image classification. We were able to determine the recall, precision, F1_score, and AUC values for each class for TL, FT for five runs because the data set utilized has seven categories, making the classification multi-class. Transfer learning (TL) is the process of using a model that was trained on a particular dataset. By starting with the model and updating and modifying its parameters to fit the recently supplied dataset, the model was re-used to solve other problems that were similar to it. TL looks for a model that is suitable for the training dataset by using learning outcomes from prior models. The output of the probabilistic results from the network's last layer is fed into the suggested model as a dataset image with dimensions of 224×224×3. Three fully-connected layers were added to the VGG19 model, followed by the removal of the final layer, Denes (1000), which lacked a fully connected classifier or layers, and the addition of a classifier for skin diseases, Denes (7), as shown in Figure 3. It was the proposed model's overall accuracy (77.2±3.9623).

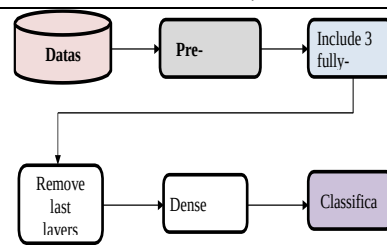


Figure 3. The architecture of the VGG19 model used

Maintaining the knowledge gained from solving one problem and applying it to another is the aim of fine-tuning. Fine-tuning is a fantastic method to enhance system performance by modifying the weights pertaining to the upper layers of pre-trained models. Setting the weight for particular layers to freeze is the first of two methods for fine-tuning. The more frozen layers there are, the less time and resources needed for fine-tuning. As an alternative, a new database may be used to train the entire architecture.

Three fully-connected layers were not included in the VGG19 model. Dense (256), global average pooling 2D, dropout (0.5), Dense (128), batch normalization layer, dropout (0.5), Dense (64), and batch normalization layer are then added, followed by the classifier Skin diseases. Dense (7) As seen in figure 4, a model was created that provided a greater overall accuracy of 82.4 ± 1.949359 . This model was superior to the model used in the transfer learning.

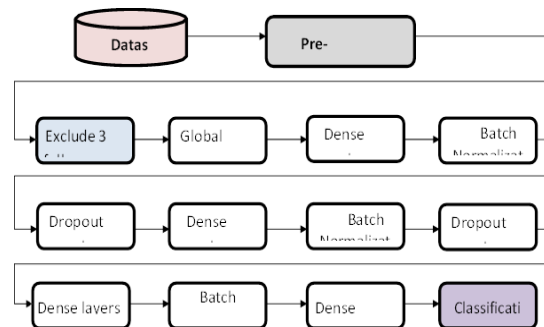


Figure 4. The architecture of the model proposed

The behavior of the model was examined following training for 60 epochs using the transfer learning approach and 100 epochs using the fine-tuning method, as illustrated in Figure 5. ROC curves for (a) transfer learning and (b) fine-tuning are shown in Figure 6. The real positive rate is shown on the vertical axis, while the false positive rate is shown on the horizontal axis. Better performance and progress upon fine-tuning are indicated by a higher AUC.

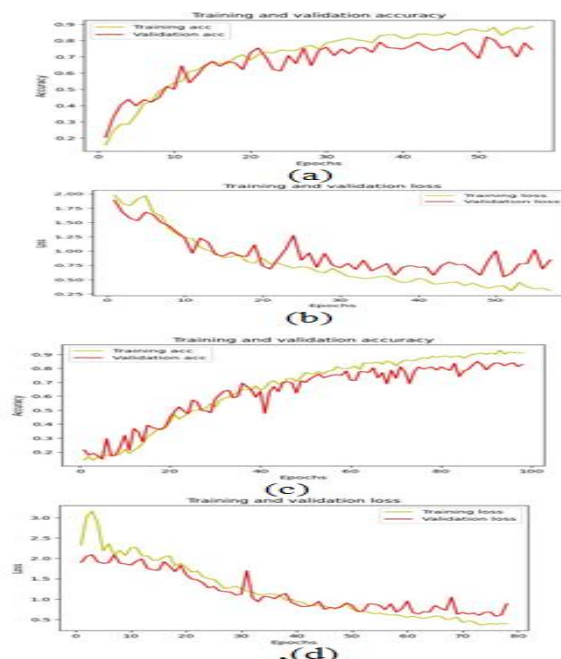


Figure 5. (a) Accuracy of transfer learning, (b) Loss of transfer learning, (c) Accuracy of Fine-tuning, (d) Loss of Fine-tuning
The confusion matrix for (a) transfer learning and (b) fine-tuning is shown in Figure 7. The model's classification performance

and mistake kinds are revealed via the confusion matrix, which shows the true positives, true negatives, false positives, and false negatives. As indicated in Table 2, the metrics for classification jobs completed were also used to assess the model's performance.

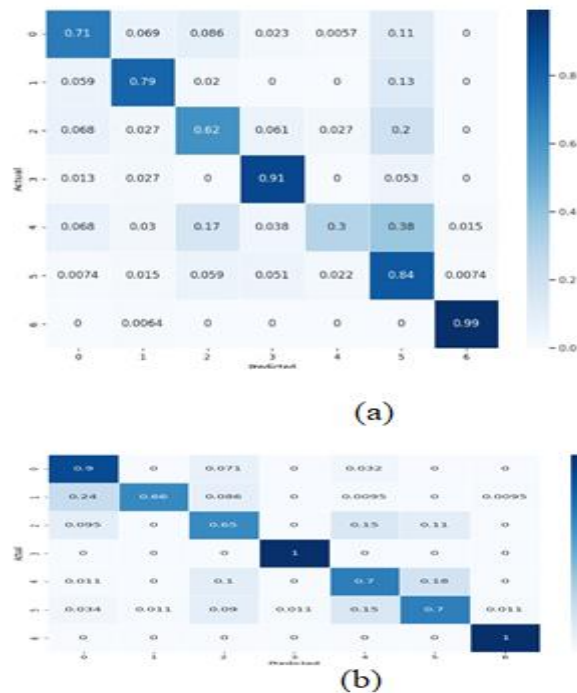


Figure 7. The confusion matrix of (a) transfer learning, (b) Fine-tuning Systematics of the Article

Table 2. Results of transfer learning and Fine-tuning

Excute	Class		Transfer learning					Fine-tuning			
		Pres.	Rec.	F1	AUC	Acc.	Pres.	Rec.	F1	AUC	Acc.
1	0	0.80	0.71	0.75	0.96	0.74	0.75	0.90	0.82	0.97	0.81
	1	0.82	0.79	0.80	0.98		0.99	0.66	0.79	0.99	
	2	0.65	0.62	0.64	0.93		0.64	0.65	0.65	0.95	
	3	0.84	0.91	0.87	0.99		0.99	1.00	1.00	1.00	
	4	0.83	0.30	0.44	0.91		0.66	0.70	0.68	0.96	
	5	0.47	0.84	0.60	0.93		0.70	0.70	0.70	0.93	
	6	0.98	0.99	0.99	1.00		0.98	1.00	0.99	1.00	
2	0	0.89	0.73	0.80	0.98	0.82	0.96	0.78	0.86	0.96	0.83
	1	0.80	0.92	0.85	0.99		0.89	0.85	0.87	0.99	
	2	0.69	0.73	0.71	0.95		0.64	0.79	0.71	0.95	
	3	0.91	0.99	0.95	1.00		0.94	1.00	0.97	1.00	
	4	0.65	0.65	0.65	0.94		0.62	0.70	0.66	0.96	
	5	0.81	0.72	0.76	0.95		0.77	0.65	0.71	0.93	
	6	0.98	0.99	0.98	1.00		0.97	1.00	0.98	1.00	
3	0	0.74	0.90	0.81	0.98	0.81	0.89	0.77	0.83	0.95	0.83
	1	0.80	0.88	0.84	0.98		0.89	0.90	0.89	0.98	
	2	0.77	0.56	0.65	0.94		0.59	0.86	0.70	0.95	
	3	0.95	0.93	0.94	0.99		0.99	0.96	0.97	1.00	

	4	0.68	0.60	0.64	0.94		0.75	0.57	0.65	0.95	
	5	0.73	0.78	0.75	0.95		0.78	0.70	0.73	0.94	
	6	1.00	0.96	0.98	1.00		0.96	1.00	0.98	1.00	
4	0	0.90	0.52	0.66	0.94	0.75	0.87	0.86	0.86	0.97	0.85
	1	0.77	0.88	0.82	0.98		0.91	0.88	0.89	0.99	
	2	0.52	0.69	0.59	0.91		0.68	0.79	0.73	0.95	
	3	0.93	0.93	0.93	1.00		0.98	0.99	0.99	1.00	
	4	0.53	0.68	0.59	0.93		0.70	0.68	0.69	0.96	
	5	0.80	0.70	0.75	0.94		0.80	0.72	0.76	0.94	
	6	0.99	0.89	0.94	1.00		0.98	1.00	0.99	1.00	
5	0	0.78	0.79	0.79	0.96	0.74	0.83	0.65	0.73	0.96	0.80
	1	0.78	0.70	0.74	0.96		0.78	0.89	0.83	0.98	
	2	0.46	0.90	0.61	0.94		0.78	0.59	0.67	0.94	
	3	0.93	0.81	0.87	0.99		0.99	0.95	0.97	1.00	
	4	0.68	0.44	0.53	0.93		0.53	0.91	0.67	0.96	
	5	0.91	0.59	0.71	0.94		0.85	0.63	0.72	0.93	

IV. Conclusion

Skin cancer is among the most prevalent and harmful cancers. Ocular diagnostics are the primary method used by dermatologists to diagnose this illness. The fine-grained diversity in the appearance of its various diagnostic categories makes multiclass skin cancer categorization a difficult process. In recent research, however, CNNs have outperformed dermatologists in the multiclass classification of skin cancer. We carried out pretreatment procedures such data balance, data labeling, and data normalization in order to help this effort, as well as resizing each image to meet the specifications of each model. We trained VGG19 by fine-tuning CNNs and applying TL to pre-trained ImageNet weights using the HAM10000 dataset. In order to investigate the effects of TL and FT, we evaluated VGG19's performance on such multiclass classification tasks using measures such as recall, precision, F1 Score, accuracy, and confusion matrices. With FT, the best performance was noted. The high classification results were a result of several aspects, including as the usage of resolution scaling, image preprocessing, data augmentation, effective TL of ImageNet weight, and FT.

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