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Deep Learning-Based Classification of Dermoscopic Images for Skin Lesions

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ABSTRACT

Skin cancer has emerged as a grave health concern leading to significant mortality rates. Diagnosis of this disease traditionally relies on specialist dermatologists who interpret dermoscopy images using the ABCD rule. However, the integration of computer-aided diagnosis technologies is gaining popularity as a means to assist clinicians in accurate skin cancer diagnosis, overcoming potential challenges associated with human error. The objective of this research is to develop a robust system for the detection of skin cancer by employing machine learning algorithms for skin lesion classification and detection. The proposed system utilizes Convolutional Neural Network (CNN), a highly accurate and efficient deep learning technique well-suited for image classification tasks. By using the power of CNN, this system effectively classifies various skin diseases in dermoscopic images associated with skin cancer The MNIST HAM10000 dataset, comprising 10015 images, serves as the foundation for this study. The dataset encompasses seven distinct skin diseases falling within the realm of skin cancer. In this study, diverse transfer learning methods were used and evaluated to enhance the performance of the system. By comparing and analyzing these approaches the highest accuracy rate was obtained using the MobileNetV2 model with a rate of 80.79% accuracy.

Keywords: Convolutional Neural Network, Transfer Learning, Image Classification, Skin Cancer

1. Introduction

Skin cancer is the most common type of cancer worldwide, and melanoma is the deadliest form. Cancer, as a term, refers to a malignant tumor that develops when cells in an organ or tissue divide and multiply irregularly. Skin cancer occurs when skin cells grow abnormally, and melanoma is defined as a type of skin cancer resulting from uncontrolled division and proliferation of these cells. Early detection of such skin cancers increases the likelihood of successful treatment.

There are two examination methods commonly used by doctors for skin diseases. One of them is dermoscopy, also known as dermatoscopy, which involves superficial microscopic inspection of the skin. It is used to identify abnormalities in moles and other skin lesions. This type of examination magnifies moles and allows for accurately evaluating subtle details that are not visible to the human eye. Dermoscopy can be performed using a handheld device or by capturing images through computerized systems. It is a frequently preferred diagnostic method because it provides early diagnosis without causing any adverse side effects.

The other method is histopathological examination, which employs various techniques to examine changes in organs, tissues, and cells under a microscope. The tissues to be studied are first sliced into suitable thicknesses using a small cutting

instrument called a microtome. They are then evaluated in a laboratory by doctors. This method is a critical diagnostic tool for confirming the diagnosis of melanoma.

When diagnosing malignant melanoma, dermatologists examine the blemish on the skin with the eye or pre-taken photographs of the blemish and look at four essential parameters. These parameters are called the ABCD rule. ABCD rule is applied for easy detection of differentiation in the follow-up of moles.

- A (Asymmetry): If one half of the mole is not similar to the other half (in terms of color and/or shape)
- B (Border): If the borders of the mole are irregular (indented)
- C (Color): If the color of the mole is not homogeneous (two or more colors such as brown, black, red, gray, and white are present together or if there is a mottled appearance)
- D (Diameter/Diameter): If the diameter of the mole is larger than 6 mm (roughly larger than the diameter of an eraser pencil) [1,2].

In this study, transfer learning models of CNN that analyze skin lesion images and classify them according to seven skin diseases were tested using a publicly available dataset. The results obtained with different models and parameters are added to the table in detail.

2. Literature Review

In the realm of dermatology research, a multitude of studies have been conducted regarding skin diseases. Kiran Pai and Anandi Giridharan embarked on a study where they employed CNNs to discern and accurately diagnose seven distinct types of skin lesions. A web application has been developed to accurately predict the top three potential types of skin lesions for a given image and present the corresponding top three classes. The model was trained using VGGNet, a transfer learning method based on the CNN architecture, carefully selected for its effectiveness and reliability in achieving optimal performance. The model was trained for 50 epochs on the HAM10000 dataset [3], yielding a test accuracy of 78 percent. Ketut Eddy Purnama et al. suggested an advanced system for precisely classifying and detecting skin diseases. Using CNN with the InceptionV3 model, dermatological diseases in dermoscopic images were accurately classified. The web classifier utilizing the CNN Inception V3 model achieved an impressive accuracy of 72 percent, while the web classifier using the MobileNetV1 model attained a good accuracy of 58 percent [4].

Harsh Gupta et al. embarked on a comprehensive study to analyze images depicting infected regions of the skin and, additionally, classify skin cancer into a unified category. A range of pre-processing techniques were used on the skin cancer images. By harnessing the power of CNN and leveraging transfer learning models, the accuracy of the classification process was significantly enhanced. Utilizing EfficientNet B1, an outstanding accuracy rate of 94.1 percent was accomplished [5]. Xingmei Cao et al. opted for generating mixed skin lesion images to address the data imbalance issue. This method is a variation of Mask Recurrent Convolutional Neural Network (Mask R-CNN), and it involves the creation of a melanoma detection framework. Through the utilization of Mask R-CNN alongside the concept of community learning, the accuracy of the generated classification was experimentally enhanced by 2.56 percent. The study was conducted on the ISIC dataset, and the proposed algorithm achieved an accuracy of 90.61 percent [6]. Attik et al. suggested a computer-aided diagnosis (CAD) system based on deep learning. RGB images were used to train the Mask R-CNN model. The ISBI2016 and ISIC2017 datasets were selected for these images. The Least Squares Support Vector Machine (LS-SVM) technique was also employed. Three distinct datasets (ISBI2016, ISBI2017, and HAM10000) were utilized for validation. The obtained accuracies were 96.3%, 94.8%, and 88.5%, respectively [7]. Khan *et al*. presented a state-of-the-art deep learning framework, leveraging Mask R-CNN for precisely segmenting and classifying skin lesions. This framework surpasses existing techniques in sensitivity, precision, F1 score, and accuracy [8], establishing itself as a significant breakthrough in dermatological research. Srivastava et al. proposed a texture based feature extraction framework for classifying dermatoscopic images of skin cancer. For their technique, the average accuracy, average precision, and average recall value were found to be 96%, 95.44% and 75.20%, respectively [9]. Alam et al. proposed a skin cancer classifier based on deep learning for the HAM10000 dataset. They found that in both unbalanced and balanced datasets, the results of RegNetY-320 outperformed those of AlexNet and InceptionV3 in terms of receiver operating characteristic (ROC) curve, F1 score and accuracy [10]. Bassel et al. suggested a hybrid deep learning model for the automatic classification of benign and malignant skin cancers using various methods such as Resnet50, Xception, and VGG16. The proposed method achieved 90.9% accuracy and could provide a robust and reliable classification system with a large training dataset [11]. Salma and Eltrass presented an automated CAD system for the classification of skin lesions using deep learning techniques. The paper also mentions the use of dermoscopy, a noninvasive skin imaging technique, for early identification of skin cancer [12]. Shetty et al. focused on the classification of skin lesions using machine learning and CNN. The paper concluded that CNN provides better accuracy compared to other machine learning algorithms used in their work [13]. Aladhadh et al. suggested a two-tier framework for the classification of skin cancer using Medical Vision Transformer (MVT) and data augmentation techniques. In their study, the MVT-based model achieved better results than other techniques for skin cancer classification [14]. Iqbal et al. proposed a hybrid approach using CNN and local binary patterns (LBP) for the classification of melanoma images. The approach was evaluated on publicly accessible datasets and

showed promising results with an average sensitivity of 95.63%, accuracy of 97.29% and specificity of 97.90% [15]. Ahmad et al. developed hybrid techniques SVM-MobileNet, SVM-ResNet101and SVM-MobileNet-ResNet101 to classify two datasets, HAM10000 and PH2, of skin lesions. Their results showed better performance than pre-trained CNN models [16]. Alwakid et al. employed Inception-V3 and Inception Resnet-V2 models for melanoma recognition using the HAM10000 dataset. Their models performed the results of 0.89 for Inception-V3 and 0.91 for InceptionResnet-V2 [17].

3. Methodology

3.1. Convolutional Neural Network (CNN)

CNNs are improved versions of Artificial Neural Networks (ANNs). CNNs expand on the concept of ANNs by increasing the depth of the network through the addition of more hidden layers. CNNs can be seen as an example of this deepening network structure.

The key difference that sets CNNs apart from ANNs is the use of the DropOut method in CNNs, which helps prevent overfitting and memorization during the training process. By dropping out randomly selected neurons during training, CNNs encourage the network to learn more robust and generalizable features.

The architecture of CNNs forms the foundation of the Deep Learning concept. It consists of various layers that perform different tasks in a sequential manner. The initial stages involve Convolutional and Pooling layers, which extract important features from the input data (such as images) in a hierarchical manner. These layers capture local patterns and gradually build up a more abstract representation of the data.

The last phase of a CNN typically involves Fully Connected layers, which connect all the neurons from the previous layers to form a dense network. It is followed by a Classification layer that produces the final output, usually in the form of probabilities for different classes or categories.

In summary, CNNs can be viewed as a series of trainable components arranged in a sequential manner, with an informative classifier at the end. The training process occurs through layer-by-layer processing as the input data flows through the network. Eventually, a final output is generated, and a comparison is made with the correct result to evaluate the performance of the network.

CNNs, like CNNs, can handle various types of input data, including signals such as audio, images, or videos. This flexibility allows CNNs to be applied to a wide range of problems across different domains [18].

Figure 1 shows the general overview of a CNN architecture. The layers used in a CNN are Convolution Layer, ReLU, Pooling Layer, Fully Connected Layer, DropOut Layer and Classification Layer, respectively. Convolution Layer is the layer that forms the basis of CNN. This operation is done by applying a specific filter over the entire image.

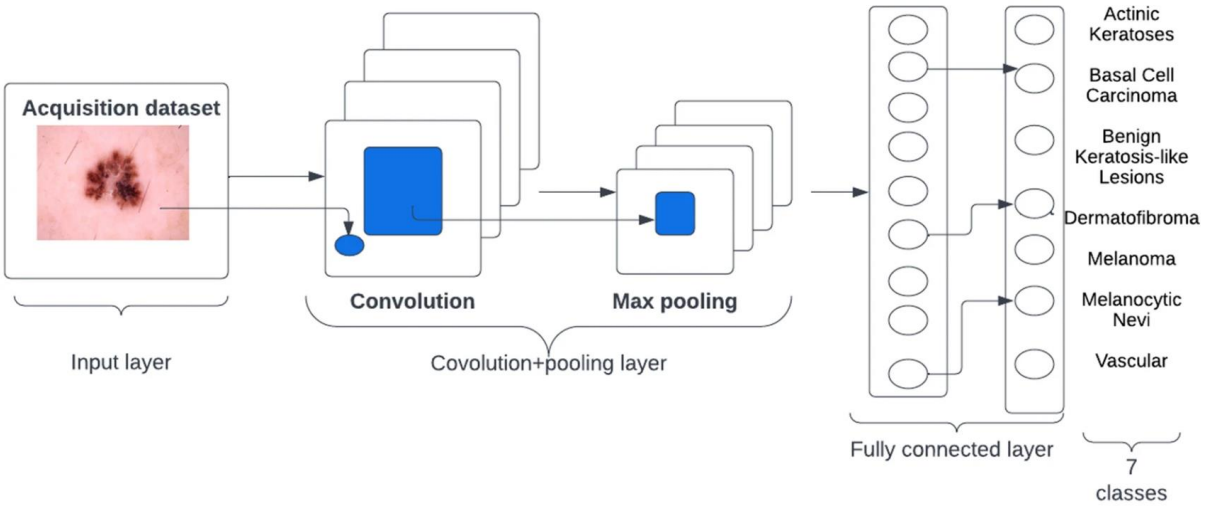

Figure 1 Overview of CNN Architecture [13]

ReLU is the most often utilized rectifier unit for CNN neuron outputs and comes after the convolution layers. Pooling Layer usually occurs after the ReLU layer. Its primary goal is to lower the input size (Width x Height). Fully Connected Layer is connected to all areas of the previous layer, and it works on an input where each input is connected to all neurons. DropOut Layer is used to prevent the network from memorizing and some nodes of the network are removed in this layer. Classification is done in the Classification Layer. This layer's output value and the number of objects to be categorized are both equal [19].

3.2. Dataset

The images used in this study were taken from the “Skin Cancer MNIST: HAM10000” dataset [20]. The HAM10000 dataset is a widely used dataset in the field of dermatology and machine learning. It stands for "Human Against Machine with 10000 training images" and consists of a collection of 10015 images of skin lesions. The dataset was created to facilitate the research and development of automated algorithms for the diagnosis of skin cancer.

Each image in the HAM10000 dataset is accompanied by various metadata, including information such as the lesion's clinical diagnosis, anatomical location, patient information, and other attributes. The dataset covers a range of skin lesion types, including melanoma and other types of benign and malignant lesions.

Researchers and developers often use the HAM10000 dataset to train machine learning models or develop computer vision algorithms that can accurately classify and diagnose skin lesions. The goal is to create automated systems that can assist dermatologists in the early detection and diagnosis of skin cancer, potentially improving patient outcomes and reducing the burden on healthcare systems.

It's important to note that while the HAM10000 dataset is a valuable resource, any real-world application of machine learning algorithms for medical diagnosis should involve rigorous validation, clinical studies, and integration with healthcare professionals to ensure safety and accuracy. The sample skin lesion types collected from the HAM10000 dataset are shown in Figure 2. These skin lesion types include cases belonging to seven different classes. In the dataset, the HAM10000_metadata.csv file contains all the information about the lesions, such as classes and properties. These classes are akiec, bcc, bkl, df, mel, nv and vasc, respectively.

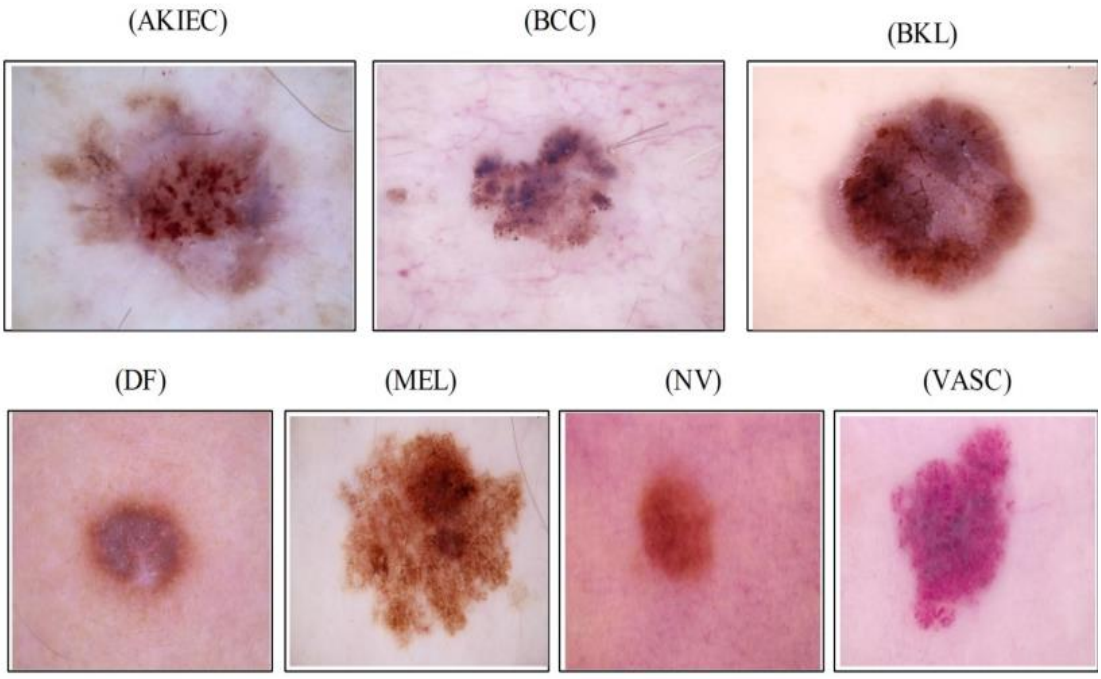

Figure 2 Sample skin lesion types collected from the HAM10000 dataset [20]

3. 3. Data Augmentation

Data augmentation is the process of adding data to enhance the number of data to be used. In the data augmentation procedure, the new data is added to the training data. New data is created by changing the attributes of images, such as horizontal/vertical rotations, brightness changes, horizontal /vertical shifts and zoom [21, 22]. Figure 3 shows the augmentation techniques applied in this study and an example result on an original image. The classes applied to images from the data augmentation techniques listed in Figure 3 are shown in Table 1.

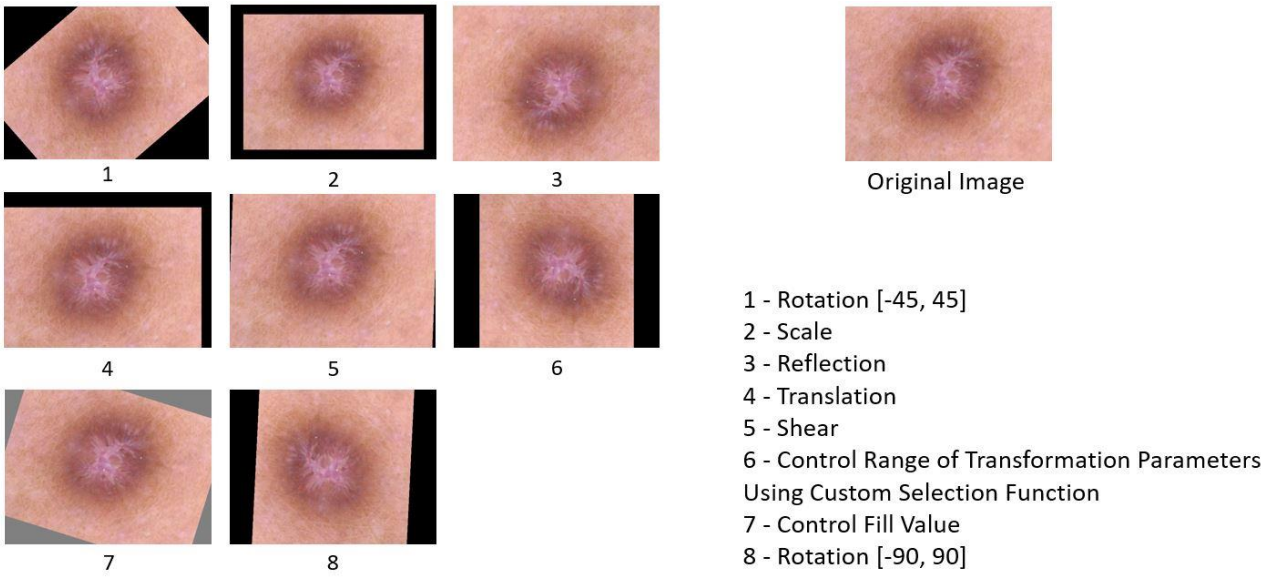

Figure 3 Data augmentation techniques applied in this study and an example result on an original image.

The alternative purpose of the data augmentation process is to balance the amount of data for each class of dataset. As can be seen in Table 1, the distribution of the number of images of the lesions is quite irregular. While the total number of images of the Melanocytic Nevi (nv) skin disease class in Table 1 is 6705, the total number of images of the Dermatofibroma (df) skin disease class is 115. There are several methods to balance this situation. In this study, 1000 images from each class were used. In the classes with a sufficient number of images, 1000 images were randomly selected, and in the other classes, the number of images was increased using augmentation. As stated in Table 1, 7000 images constitute our dataset.

Table 1 Image distributions of the dataset before and after augmentation

Skin Lesion	**Number of Images (Before Augmentation)**	**Balanced Number of Images (After Augmentation)**	**Type of Augmentation Technique**
Melanocytic Nevi (nv)	6705	1000	None
Melanoma (mel)	1113	1000	None
Benign Keratosis (bkl)	1099	1000	None
Basal Cell Carcinoma (bcc)	514	1000	1
Actinic Keratoses (akiec)	327	1000	1,2 and 3
Vascular Lesions (vas)	142	1000	1,2,3,4,5,6 and 7
Dermatofibroma (df)	115	1000	1,2,3,4,5,6,7 and 8
Total	10015	1000	

4. Experimental Observations and Results

First, the increased dataset is divided into three parts: training, testing and validation. As a result of pre-processing, each class consists of 1000 images. It was found appropriate to allocate 70% of the images for training, 20% for testing and 10% for validation. Thus, for each class, there are 700 images in the training set, 200 images in the test set, and 100 images in the validation set. It should be noted that none of the images reserved for training or the reproduced versions of that image with data augmentation methods are not included in the test images or validation images. That is, the images of the training group, test group and validation group do not have the same or similar images.

As indicated in Table 2, many Transfer Learning (TL) models have been tested with our dataset. Early stopping criteria is applied during the training phase. In this way, if it is noticed that there is no increase in accuracy with the patience value entered as a parameter, the training is completed without waiting until the entered epoch value. Table 2 also indicates how many steps each model terminates. Another parameter is the trainable status of the feature extraction layers transferred from pre-trained models. In the model, the trainable part is tested separately as both false and true and added to the table. In addition, two different frameworks were used. One of them is TensorFlow and the other is PyTorch. It is seen that the highest accuracy values are reached when PyTorch is selected as the framework and True is selected as trainable. While there is no significant difference between True and False values in TensorFlow, there is quite a difference between True and False in PyTorch.

After trial and error processes, we determined appropriate hyperparameters such as learning rate and optimizer. SGD is used for optimization during the training, and the learning rate is set to 0.001. Cross entropy loss is used to measure the error between prediction and real class values. We did not use a fixed number of epochs, as we ended the training process by looking at validation. The training was terminated automatically according to the validation loss value via early stopping.

Table 2 Applied Transfer Learning models and results

TL Model	Number of epochs	Accuracy	Trainable	Framework
VGG16	13	57%	FALSE	TensorFlow
VGG16	25	54.57%	TRUE	TensorFlow
ResNet50V2	12	62.71%	FALSE	TensorFlow
ResNet50V2	27	38.43%	TRUE	TensorFlow
MobileNet	12	61.64%	FALSE	TensorFlow
MobileNet	25	70.36%	TRUE	TensorFlow
MobileNetV2	14	63.36%	FALSE	TensorFlow
MobileNetV2	25	55%	TRUE	TensorFlow
DenseNet169	12	59.07%	FALSE	TensorFlow
DenseNet169	25	48.43%	TRUE	TensorFlow
NASNetMobile	12	56.36%	FALSE	TensorFlow
Xception	14	58.64%	FALSE	TensorFlow
Xception	29	68.43%	TRUE	TensorFlow
InceptionResNetV2	11	60.5%	FALSE	TensorFlow
InceptionResNetV2	16	73%	TRUE	TensorFlow
VGG19	19	62.43%	FALSE	TensorFlow
ResNet18	18	66.71%	FALSE	PyTorch
MobileNetV2	20	65.86%	FALSE	PyTorch
EfficientNetB0	27	66.21%	FALSE	PyTorch
InceptionResNetV2	22	60.07%	FALSE	PyTorch
ResNet18	19	79.43%	TRUE	PyTorch
MobileNetV2	**22**	**80.79%**	**TRUE**	**PyTorch**
EfficientNetB0	23	79.71%	TRUE	PyTorch
InceptionResNetV2	24	76.43%	TRUE	PyTorch

Since the highest accuracy rate was obtained with the MobileNetV2 model, the accuracy and loss graphs of this model are shown in Figure 4. As can be seen from the graphs, the training was completed automatically at 22 epochs since there was no change in the values.

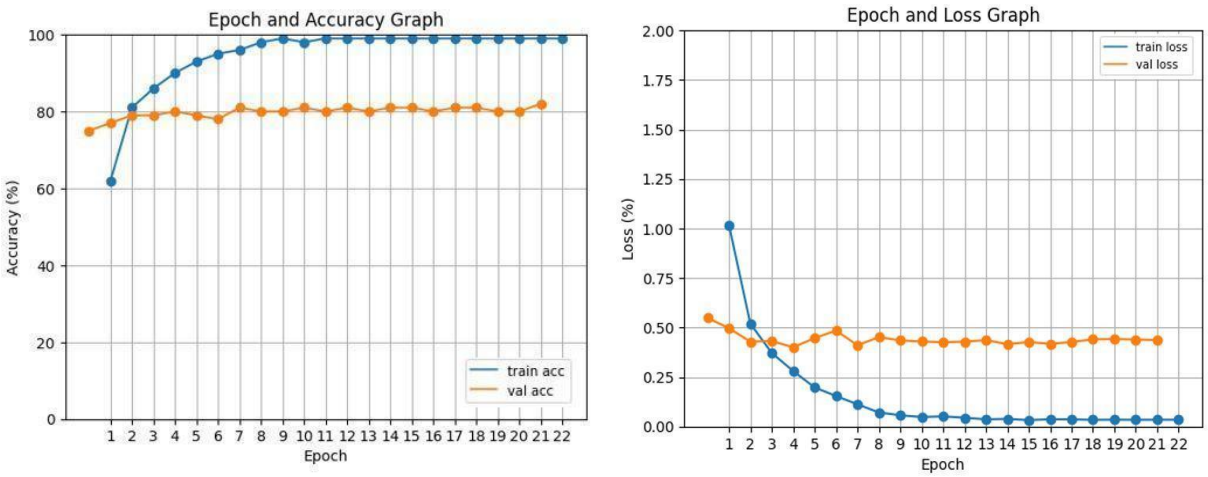

Figure 4. Accuracy and loss graph of MobileNetV2

Figure 5 shows the confusion matrix created for the seven lesion classes in the data set for MobileNetV2. In the confusion matrix, label 0 indicates akiec lesion, while label 6 indicates vasc lesion. Other labels also continue in alphabetical order as Table 1. Mel indicated with label number 4 is the lesion class with the lowest accuracy value, with an accuracy value of 59%. Vasc indicated with label number 6 is the lesion class with the highest accuracy value of 93%.

Figure 5. Confusion Matrix of MobileNetV2

Table 3 shows the comparison of our study with other studies in the literature. It is not correct to make a complete comparison here because the number of classes and data numbers in other studies are different from each other.

Table 3 Comparison with other studies in the literature

Reference	Year	Method	Dataset	Accuracy
[1]	2020	Decision Tree	ISIC	80%
[2]	2017	Support Vector Machine	ISIC and Skinvision website	92.1%
[3]	2019	VGGNet CNN	HAM10000	78%
[4]	2019	InceptionV3	HAM10000	72%
[5]	2020	EfficientNetB1	HAM10000	94% (F1-Score)
[6]	2021	Mask R-CNN	ISIC2017 and ISIC2018	90.61%,
[7]	2021	MASK RCNN-DenseNet	ISBI2016, ISBI2017 and HAM10000	96,3%
[8]	2021	Mask R-CNN	PH2, ISBI2016, ISIC2017 and HAM10000	86,5%
[9]	2022	M-QuadLTQP with CNN	HAM10000 and ISICUDA11	96%
[10]	2022	RegNetY320	HAM10000	91%
[11]	2022	StackingCV	ISIC	90.9%
[12]	2022	ResNet50+SVM	ISIC2017 and HAM10000	99.87%
[13]	2022	Machine Learning+CNN	HAM10000	95.18%
[14]	2022	MVT(Medical Vision Transformer)+MLP	HAM10000	96.14%
[15]	2022	LBPCNN	ISIC2017, ISIC2018, ISIC2019 and HAM10000	97.29%
[16]	2023	MobileNet+Handcrafted	HAM10000 and PH2	100%
[17]	2022	InceptionResNetV2	HAM10000	91.26%
Ours	2023	MobileNetV2	HAM10000	80.79%

5. Conclusions

Skin cancer is a common and serious disease that can cause death if left untreated. When skin cancer is detected early from dermatoscopic images, the probability of definitive treatment is high. Manual diagnosis of skin cancer is a time- and cost-intensive process. Therefore, it is of great importance to develop automatic diagnostic methods to classify multiclass skin lesions with higher accuracy. Recently, deep learning-based models have demonstrated above-human-level accuracy in classification tasks. CNNs outperform human vision and can significantly reduce a dermatologist's or specialist's efforts to predict a possible worsening. In this study, seven different skin cancer types in the MNIST HAM10000 dataset were classified and compared using different CNN models. Since the HAM10000 dataset is unbalanced, the data augmentation process was done in a balanced way before the classification. The highest accuracy rate was obtained with the MobileNetV2 model. The observed 80.79% accuracy when tested with real samples may not be sufficient. This ratio is clearly due to the imbalance in the number of images belonging to the classes, since the total number of images of the Melanocytic Nevi (nv) skin disease class is 6705, while the total number of images of the Dermatofibroma (df) skin disease class is 115. Adding new images to skin disease classes with a low number of images can increase the accuracy and reliability of the model. In addition, the accuracy values can be increased when pre-processing methods such as hair removal and contrast stretching are applied to the images while editing the data set. Hybrid models can also be tried to achieve higher results in future studies.

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Conflict of Interest Notice
The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical Approval and Informed Consent
It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

Availability of data and material
Not applicable

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