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An Efficient Approach for Automatic Melanoma Detection Based on Data Balance and Deep Neural Network

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ABSTRACT

One of the most serious types of skin cancer is Melanoma, which can be fatal if it is not detected in its early stages. Patients need to visit a dermatologist to diagnose infected skin and determine if it is Melanoma or not. The traditional method for a dermatologist is more complicated and requires extensive experience to look at the skin with a dermatoscope and then provide a biopsy report for diagnosis. Instead of traditional methods, artificial intelligence, especially deep learning, provides powerful results in experience-based problems without the need for experts in the specific field of the problem. For this reason, deep neural network architectures can be useful for dermatologists and patients in the early stages of identifying melanoma skin cancer. This paper offers a proposed approach for automatically classifying Melanoma using convolution neural network (CNN) architectures VGG19 and GoogleNet. From data balance for input images, which makes a huge difference in results to preprocessing images and testing VGG19, GoogleNet in the feature extraction process and final binary classification with class 1 means Melanoma and class 0 means nonmelanoma. A dataset was used from the international skin imaging collaboration datastores (ISIC 2019) with 7146 total used images. Proposed approach results show that GoogleNet accuracy is 80.07 % and 81.28% in the training and testing dataset, and VGG19 accuracy is 85.57 % and 78.21 % in the training and testing dataset.

1. Introduction

Worldwide, cancer is one of the most common diseases leading to death. One of the most dangerous types of cancer is skin cancer. Skin cancer has three major malignant types: Melanoma, basal cell carcinoma (BBC), and squamous cell carcinoma (SCC) [1]. Melanoma is the 17th most common cancer worldwide, with 324,635 diagnosed cases, 173,844 in men and 150,791 in women in 2020 [2]. Nonmelanoma skin cancer also had high numbers of diagnosed cases; only in 2020, about 1,198,073 cases were detected, 722,348 for men and 475,725 for women [2]. Skin cancer mortality in 2020 for Melanoma is 57,073 cases of death, and nonmelanoma is 63,731 cases of death [2]. The American Cancer Society organization estimates for Melanoma in the United States, in 2023, about 97,610 new melanoma cases will be diagnosed (nearly 58,120 in men and 39,490 in women), and about 7,990 people are expected to die [3]. According to the World Health Organization, between 2 and 3 million nonmelanoma skin cancer and 132,000 melanoma skin cancer cases are diagnosed globally each year, and one in every three cancers is diagnosed with skin cancer [4]. Especially for Melanoma, early diagnosis is the best treatment and reduces mortality rates, so to ensure early diagnosis, the traditional methods for dermatologists can't be enough. In the traditional way to diagnose skin cancer, whether it is Melanoma or not, a skilled dermatologist will first visually examine the skin lesion, then use a dermatoscope to observe the lesion patterns in greater detail, and then provide a biopsy report to analyze infected skin cells. Depending on the dermatologist's skills and experience, this is a time-consuming and complicated process. Also, their visual examination of the skin lesion usually uses the ABCDE rule to define Melanoma from other types, which stands for asymmetry, border, color, diameter, and evolution over time [5].

Figure 1 shows five parameters of ABCDE rule which asymmetry of Melanoma is one half on the spot is not the same as the other half, the border is irregular, scalloped poorly define the border, infected skin has varying colors from one part to the next, the most common diameter of Melanoma is 6 millimeters and finally spreading of infected skin over time is a significant measure in determining it is Melanoma or not.

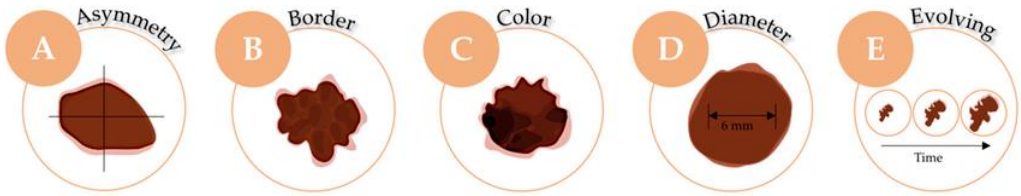


FIGURE 1. ABCDE rule of Melanoma

However, Artificial intelligence can play a significant role in the early diagnosis of Melanoma, leading to an increased survival rate. Classification methods using machine learning, including decision trees, support vector machines, and especially a part of machine learning deep learning, can be used to facilitate the diagnosis process [6-9]. Many machine-learning techniques have limitations regarding data processing and need high contrast, mostly free of noise input images. Most skin cancer datasets can't be directly suitable for these methods and need manual interaction in each preprocessing to reach suitable data inputs. On the other hand, deep learning is more powerful in handling problems with fewer preprocessing steps for input data [10-13]. One of the most common techniques in deep learning is a convolutional neural network widely used for automatic image recognition and classification without lots of preprocessing for input images. The main contributions of this paper are summarized as:

1. A proposed approach for melanoma classification is presented to enhance melanoma early diagnosis with a few requirements in the preprocessing of images. Instead of using traditional methods for melanoma detection, highly experienced dermatologists must look at the skin with a dermatoscope and then provide a biopsy report for diagnosis.
2. One of the main operations done in the proposed method is data balance, which makes a good difference in performance results. It is applied to the total number of images on each side of the class to ensure better generalization for the model.
3. The proposed approach facilitates the process of melanoma skin cancer detection using deep learning-based architectures VGG19 and GoogleNet, starting from taking input images and preprocessing of images with data splitting, image resizing, and normalization to end with modifying VGG19 and GoogleNet to classify each image.
4. We record the performance for each architecture with the ISIC 2019 dataset using standard performance measures such as accuracy, precision, recall, and f1score and compare their results with other architectures which use the same dataset source.

The subsequent sections of the paper are arranged as in the following. The next section shows the related works with summarized descriptions for each one. Section 3 delivers the proposed model. Section 4 shows the experimental results. The last section concludes the observations.

2. Related Work

Several artificial intelligence-based approaches have been proposed to automate the classification process of skin cancer diseases, especially for Melanoma, to reduce the time taken in skin cancer diagnosis. Using reported biopsy as histopathological images to determine if it is Melanoma [14] proposed an approach using the convolutional neural network ResNet50 to handle the classification of these images and compare results with expert histopathologist results. Proposed ResNet trained using 595 images from 595 individual patients (300 nevi and 295 melanoma). For testing, 100 additional images (50 nevi and 50 melanoma) were used to evaluate the performance of ResNet. Calculating misclassification rates between the average result

of ResNet and pathologist were calculated separately for Melanoma and nevi. Finally, misclassification rates of ResNet (total discordance with histopathologist) were 18% for Melanoma (95% CI: 7.4-28.6%), 20% for nevi (95% CI: 8.9-31.1%), and 19% for all set of images (confidence intervals 95% CI: 11.3%-26.7%).

The previous approach is still not approved. Artificial intelligence-based methods are better than traditional methods, especially with small data. So, another proposed approach [15] using 5,008 dermoscopic images and biopsy-proven from the International Skin Imaging Collaboration Archive (ISIC). Comparing the performance between convolutional neural network ResNet50 with dermatologists of nine German university hospitals using 4204 images for ResNet50 training, 804 Testing ResNet50 and randomly presented to dermatologists who evaluate each image. The sensitivity and specificity for classification by dermatologists were 67.2% (95% CI: 62.6%-71.1%) and 62.2% (95% CI: 57.6%-66.9%); in the other hand, ResNet50 achieved a higher sensitivity of 82.3% (95% CI: 78.3%-85.7%) and specificity of 77.9% (95% CI: 73.8%-81.8%).

Another work [16] proposes a deep learning-based data purification and augmentation approach to pass the most suitable data for a convolutional neural network, ResNet50. Using 919 images of Melanoma (803 cases from ISIC 2017, 40 cases from PH4, 76 cases from the Edinburgh dataset) and 2,518 images of nevi (2107 cases from ISIC 2017, 80 cases from PH4, 331 cases from the Edinburgh dataset) and 545 images of seborrheic keratosis (288 cases from ISIC 2017, 257 cases from the Edinburgh dataset). Data purification is performed using data processing approaches to find and remove hairs and rulers on images using a hair removal algorithm. These steps include thresholding the image's luminance channel in LUV color space and morphological processes like closing. To ensure reliable performance testing dataset that contains 600 images (117 melanoma, 90 seborrheic keratosis, and 392 nevi images) was presented to two dermatologists. The accuracy obtained from ResNet50 is 81.6% and two dermatologists have 65.56% and 66.0% accuracies.

[17] shows a ConvNet (Convolutional neural network) model based on three architectures, InceptionV3, ResNet, and VGG19, with several parameters to identify the best architecture for classifying melanoma skin cancer. The dataset used from ISIC 2019 and 2020 with 24,225 total images with two categories melanoma and nonmelanoma. Firstly, data preprocessing with resampling technique to balance the total number of images in each category and splitting into training and testing. Then, training data augmentation uses different random transformations like automatic rotation and vertical and horizontal pixel translation for each image to ensure the model's generalization in the training process. Finally, testing three architectures using different parameters like determining the training type being knowledge transfer or from scratch, layers to train can be specific layers or all of them, and learning algorithm (gradient descent,adam, RMSprop), learning rate value, activation functions and number of epochs. Best accuracy is reached with InceptionV3 architecture with 86.9%, Knowledge transfer training type, training all layers with Adam learning algorithm, and VGG19 Accuracy is 73.11%.

The authors in [18] proposed a deep learning-based approach by testing eight convolutional neural network architectures: VGG16, VGG19, DenseNet201, ResNet50V2, ResNet152V2, MobileNetV2, GoogleNet, and Xception. The dataset from the international skin imaging collaboration(ISIC 2019) with a total of 7146 images was processed for each of the eight architectures to get the best one in melanoma classification. Firstly, collecting 4522 melanoma images from ISIC 2019 (containing 25,333 total images with eight categories) and completing the rest of the images from other categories with 2624 images. Then pre-processing of images by resizing images to be 224x224, splitting data into three parts (training, validation, testing), and evaluating each architecture with input images. The approach shows that GoogleNet gets the best Accuracy result with 74.91% and 76.08% in the training and testing dataset and VGG19 accuracy is 65.5% and 68.67% in the training and testing dataset.

In the case of multiple types of skin cancer classification, authors in [19] proposed an approach for classifying images of skin lesions with seven categories: actinic keratosis, basal cell carcinoma (BCC), benign keratosis, dermatofibroma (DF), Melanoma, melanocytic nevi (NV) and vascular lesions (VASC) using raw deep transfer learning. The dataset used is HAM10000 (Human Against Machine) with a total of

10,015 images and separated as follows: 327 actinic keratosis, 514 BCC, 1099 benign keratosis, 115 dermatofibroma, 1113 melanoma, 6705 NV, and 142 VASC. Transfer learning is implemented using thirteen customized deep learning architectures like SqueezNet, GoogleNet, Xception, Inceptionv3, ResNet50, ResNet101, DenseNet201, ResNet18, MobileNetv2, Inception-ResNet, ShuffleNet, DarkNet53, EfficientNet-b0, each one evaluated separately on classifying seven skin cancer categories. Measuring the performance of each architecture using mean accuracy, precision, recall, and f-score, with different data splitting starting with 70/30 for the training dataset and testing dataset, ResNet101 achieved the best overall accuracy with 76.7%, 80/20 training and testing DenseNet201 achieved the best overall accuracy with 73.5%, 90/10 training and testing DenseNet201 achieved the best overall accuracy with 82.9%.

[20] proposed an approach for segmenting and classifying melanoma skin cancer using deep learning-based architectures. Segmentation was implemented using a feature pyramid network (FPN) merged with three architectures: MobileNet-v2, ResNet34, and DenseNet121. In this approach, semantic segmentation of skin cancer is accomplished by the FPN algorithm. This deep learning technique combines the benefits of multi-scale feature representation and convolutional neural network (CNN). To image classification, DenseNet121 architecture is used after preprocessing and segmentation of input images to determine if it contain Melanoma or not. The dataset used is HAM10000 (Human Against Machine), which contains 10,015 dermatoscopic images. Performance results for segmentation are measured using IOU scores of 80%, 75%, and 70% for ResNet34, MobileNet-v2, and DenseNet121, respectively; DenseNet121 achieves 80% accuracy in classification. Table 1 shows a summary of previous related work.

TABLE 1: Summary of Related Work

Paper	Dataset	Architectures and Method	Results
Hekler, A., 2019 [14]	Dermatohistopathologic Institute (histopathological images 695 total images)	ResNet50, expert histopathologist	MR = 18% (Melanoma) MR = 20% (Nevi) MR = 19 (All Set)
Brinker, T. J., 2019 [15]	ISIC (5,008 total images)	ResNet50, expert dermatologists of nine German university hospitals	Sensitivity =82.3%, 67.2% Specificity =77.9%, 62.2%
Bisla, D., 2019 [16]	ISIC 2017, PH4, Edinburgh dataset (3,982 total images)	Data Augmentation, purification, ResNet50, and two dermatologists	Acc = 81.6 % (ResNet50) Acc = 65.56%, 66% (experts)
Mijwil, M.M, 2021 [17]	ISIC 2019, ISIC 2020 (24,225 total images)	InceptionV3, ResNet, VGG19	Acc = 86.9% (InceptionV3) Acc = 75.31% (ResNet) Acc = 73.11% (VGG19)
Aljohani, K., 2022 [18]	ISIC 2019 (7146 total images)	DensNet201,MobileNetV2, ResNet50V2,ResNet152V2, Xception,VGG16,VGG19 and GoogleNet	Best Acc = 74.91% (GoogleNet)
Fraiwan, M., 2022 [19]	HAM10000 (10,015 total images)	Thirteen architecture (SqueezNet, GoogleNet, DenseNet201, Inceptionv3,…)	Best overall Acc = 82.9% (DenseNet121)
S. Kavitha, 2023 [20]	HAM10000 (10,015 total images)	FPN, ResNet34, MobileNet-v2, DenseNet121	Best Acc = 80% (DenseNet121)

3. Proposed Model

This paper proposes an efficient approach for melanoma classification to enhance the early diagnosis process for dermatologists and patients. Figure 2 shows the proposed melanoma classification approach using convolutional neural network architectures VGG19 and GoogleNet and key preprocessing for input images to reach the best accuracy. Starting from data balance, image resizing, and data normalization and using convolutional neural network architectures VGG19 and GoogleNet to handle binary classification of input image if it is Melanoma with two classes, 1 for Melanoma and 0 for nonmelanoma. The next subsections will discuss each step in the proposed approach.

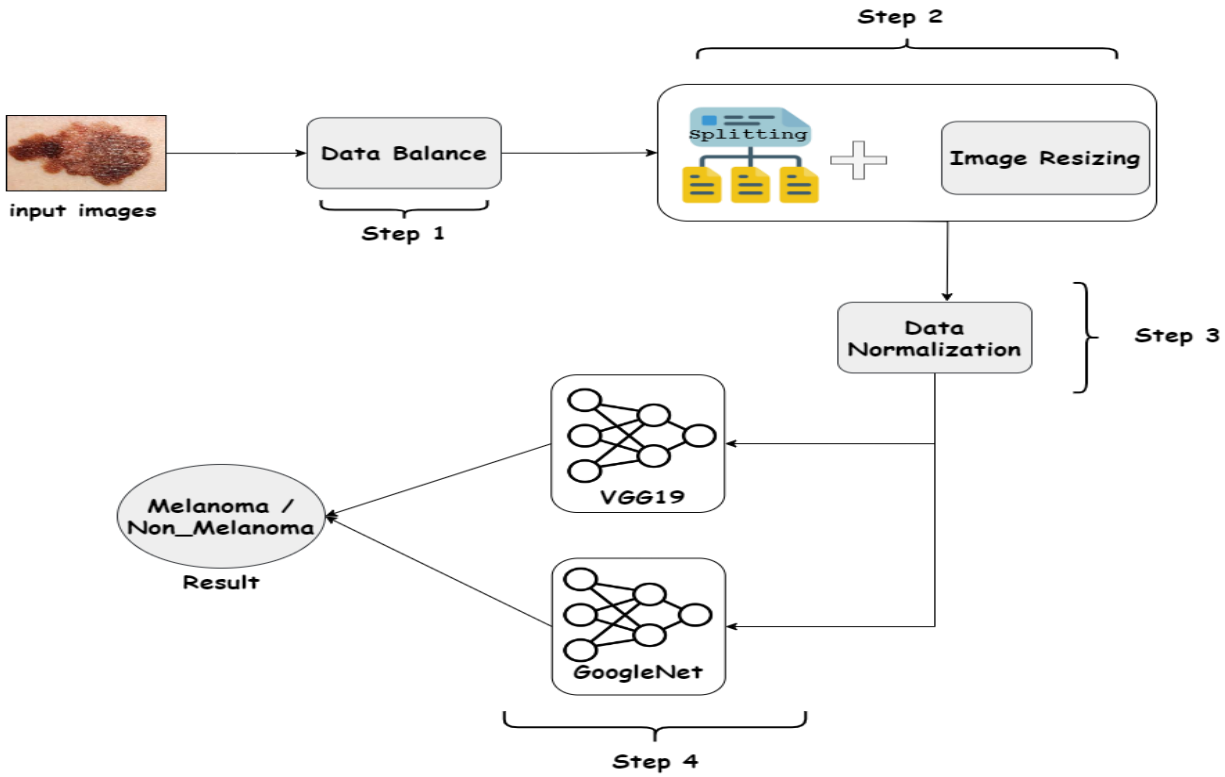
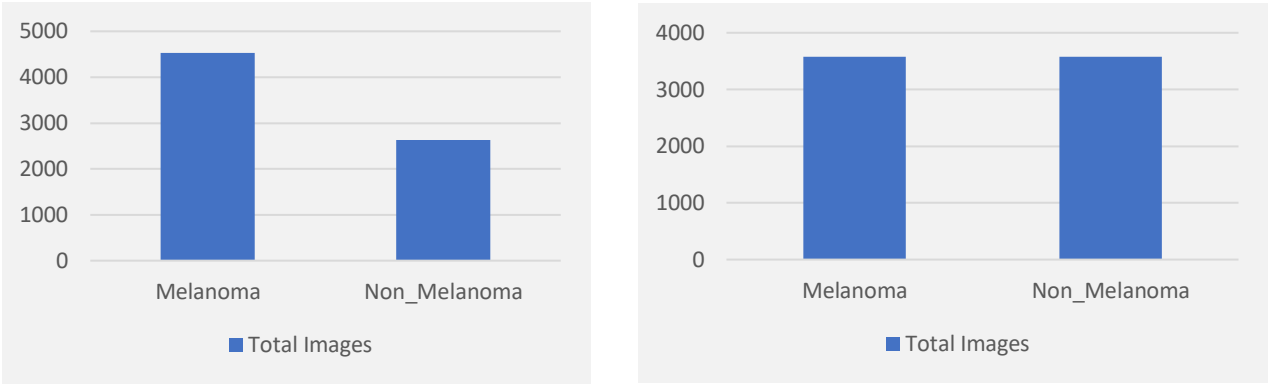


FIGURE 2. Proposed Approach for Melanoma Classification

3.1. Data Balance

The dataset contains two classes to handle Melanoma and nonmelanoma, and as shown in Figure 3(a) total number of images in each class is uneven and isn't suitable for training an artificial neural network as the artificial neural network would focus more on generalizing the majority class with a high number of images and struggle in the minority class if one of them offer a large number of images to the other. For this reason, data balance must be applied to the total number of images on each side of the class to ensure better generalization for the model. So, balancing each category with the same number of images is done from ISIC 2019 by using only 3573 random images of Melanoma and the same for non_melanoma with almost equal quantities from the other seven categories of ISIC 2019 to maintain data diversity. The result of the data balance can be seen in Figure 3(b).



(a) (b)

FIGURE 3. Data Balance for Input Images with the Total Images Number of each Class: (a) before Data Balance (b) after Data Balance

3.2. Splitting and Images Resizing

After data balance is applied dataset is split randomly into training, validation, and testing for use by convolutional neural network architectures VGG19 and GoogleNet. The first set was used to train the network containing 80% of total images (5716 images with 2858 melanoma and 2858 non_melanoma), and the validation dataset was used to track and enhance the model performance during the training phase containing 10% of total images (714 images with 357 melanoma and 357 non_melanoma). The last set evaluated the network and determined each architecture performance containing 10% of total images (716 images with 1:1 of Melanoma and nonmelanoma).

Neural network architecture receives inputs of the same size; most images have different dimensions. The larger the image size, the more details and data the network needs to deal with. For this reason, after splitting the dataset, images of all subsets were resized with fixed dimensions 224x224 for each image, as shown in Figure 4. It helps to increase the network's performance and reach the most suitable fixed size for images with the neural network model.

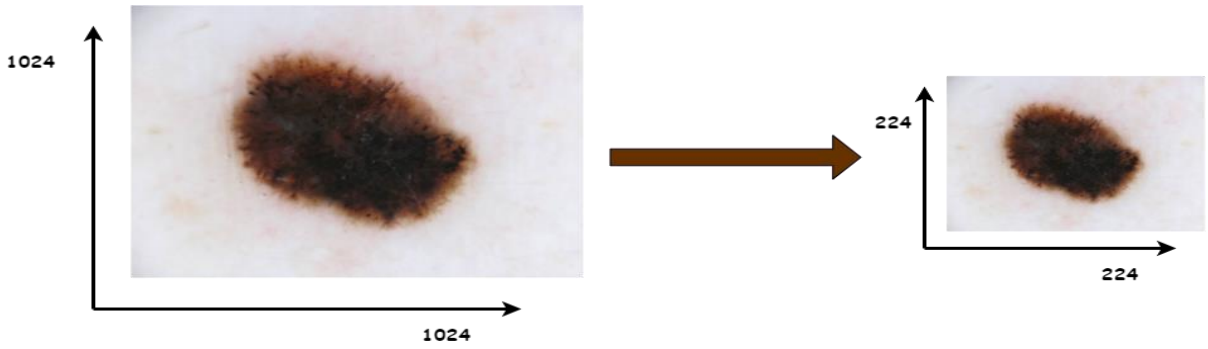


FIGURE 4. Resizing Sample

3.3. Data Normalization

Normalization of input images is one of the most important steps to increase the neural network model's performance and help it train better. As neural networks depend on gradient calculations, normalizing pixel values helps the model determine the weight or importance of a particular pixel in identifying the class of an image. It also helps gradient calculations stay consistent and prevents them from growing too large until it stops the network from training. For these reasons, after splitting the dataset each set normalized using the max pixel value in each image and implemented using python03 and TensorFlow with kears.

3.4. Convolutional Neural Network Architectures

The proposed approach uses the Convolutional neural network VGG19 and GoogleNet for applying feature extraction and classification processes. The convolutional neural network offers reliable and good performance solutions in experience-based problems using a set of convolutional and max pooling layers [21,22]. VGG19 consists of sixteen convolutional layers with five max-pooling layers for feature extraction and connected with three fully connected layers for final classification to get if the input image is a melanoma or not. GoogleNet consists of twenty-seven deep layers, including nine inception layers (the core of Goolgnet, which contains a set of convolutional and max pooling layers for feature extraction) and fully connected layers for classification. After the dataset is ready for normalization, implementation of VGG19 and GoogleNet is done using python03 with TensorFlow. The training dataset is passed to each architecture for training with changing parameters like the learning algorithm (Adam, SGD) learning rate value and the number of epochs. Finally, evaluate each model with the testing dataset to find out classification performance in determining each input if it is Melanoma or not.

4. Experimental Results

4.1. Dataset

The dataset was from the International Skin Imaging Collaboration (ISIC) version 2019 [23,24]. The objective of ISIC 2019 is to assign dermoscopic pictures (containing 25,333 images) of nine different diagnostic groups (Melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, squamous cell carcinoma and vascular) for improve skin cancer diagnosis by increasing skin imaging standards and collecting and sharing dermatologic images. From ISIC images, 7146 images were used in this approach, containing 4522 images of melanoma skin cancer and 2624 images from other categories with almost the same quantities to increase data diversity. Figure 5 shows samples of the melanoma dataset in ISIC 2019.

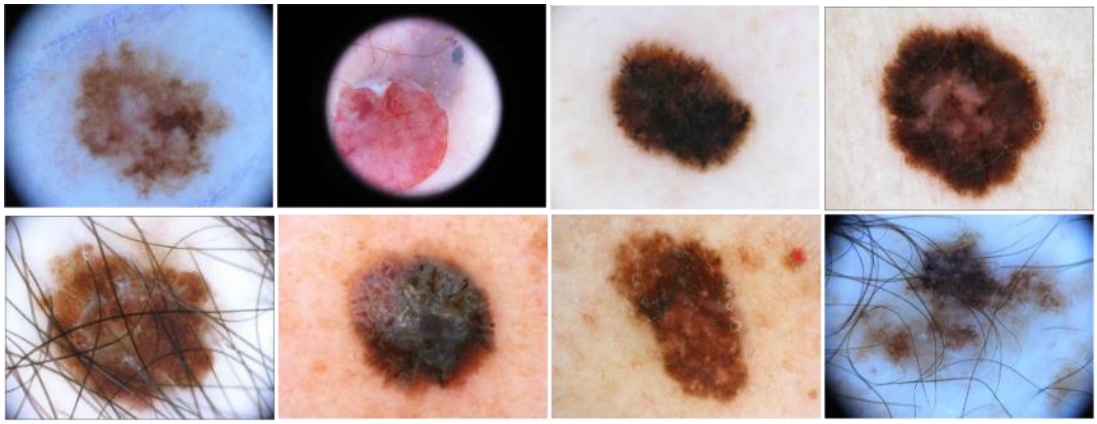


FIGURE 5. Melanoma Dataset Samples

4.2. Evaluation Approach

Different metrics, such as accuracy, precision, recall, and F1_score, are used to evaluate the results of the proposed model. The mathematical formulas used to measure each one of them are given as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\_score = \frac{2TP}{2TP+FP+FN} \quad (4)$$

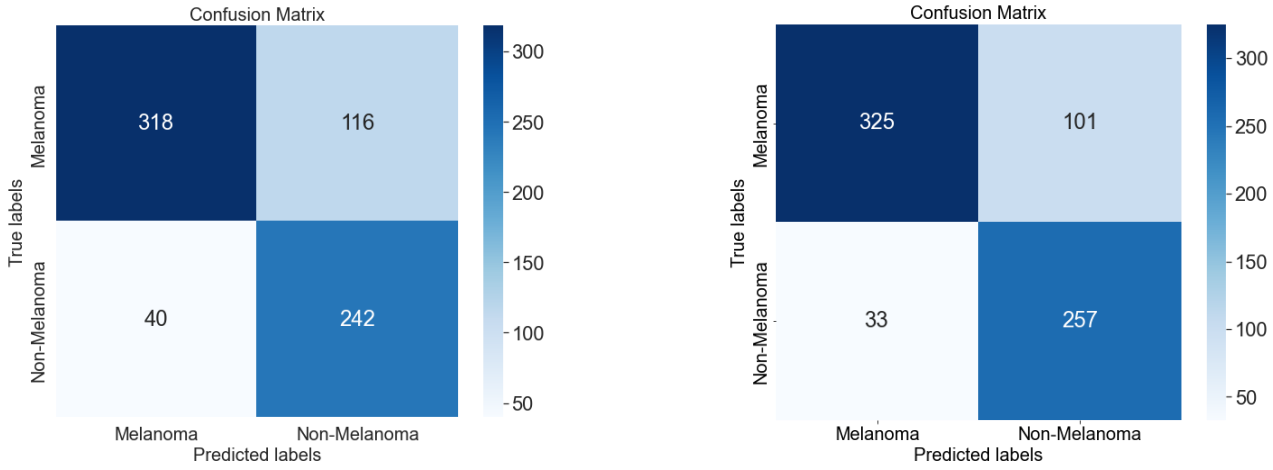
All four metrics are based on the confusion matrix result which contains four main parameters TP, TN, FP, and FN. TP stands for true positive, meaning the number of images model correctly classified it as Melanoma and images on real contain Melanoma. TN stands for true negative, meaning the number of images model correctly classified as non_melanoma and real images weren't Melanoma. FP stands for false positive, which means the number of images modeled incorrectly classified as Melanoma and real images weren't Melanoma. FN stands for false negative, meaning the number of images modeled incorrectly classified as nonmelanoma and real images containing Melanoma. Each formula is meaningful in measuring model performance; accuracy means the percentage of successfully identified samples and the overall number of predictions. As well as, precision shows a true positive ratio compared to all predicted images as Melanoma from the model, and recall shows a true positive ratio compared to all actual images containing Melanoma. The last F1-score measures the harmonic mean of precision and recall, and its value close to 1 means the model's good performance.

Table 2 shows the results of the proposed approach using VGG19 and GoogleNet. To ensure enhancement for approach, we compare the proposed approach and other State-of-Art [18] that use the same dataset source with original numbers, and our proposed architectures give better results.

Figures 6 (a), and (b) show the confusion matrix for VGG19 and GoogleNet after using the testing dataset on both. Additionally, showing training and validation accuracy progress for VGG19 in eleven epochs and GoogleNet in twenty-nine epochs, the same for loss value progress in Figure 7 and Figure 8.

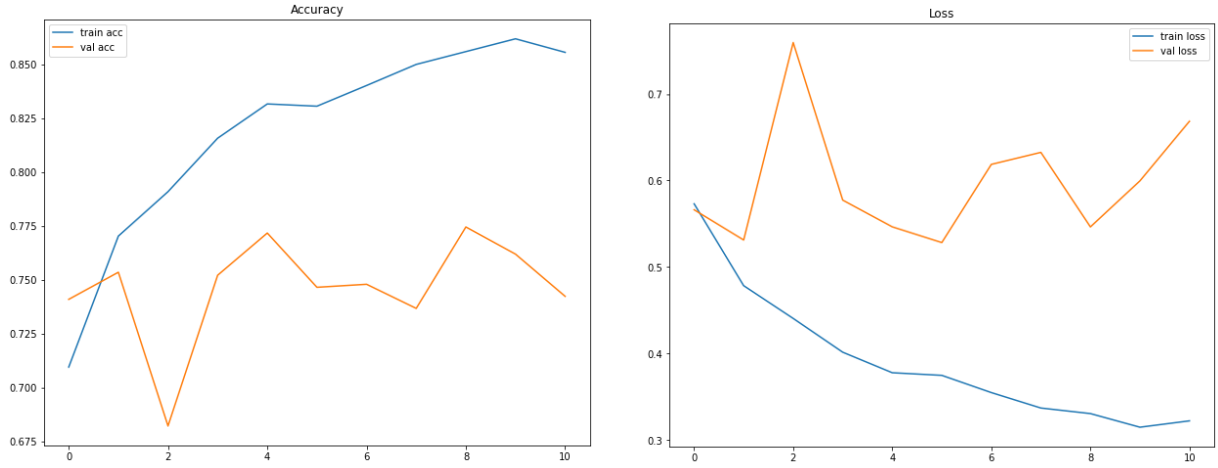
TABLE 2: Result of Proposed Model and Comparison with Other State-of-Art

Architectures in paper [18]	**Training Accuracy**	**Training Loss**	**Testing Accuracy**	**Testing Loss**	**Precision**	**Recall**	**F1_Score**
DenseNet201	73.96 %	0.516	74.68 %	0.517	78 %	85 %	81 %
MobileNetV2	71.88 %	0.537	73.98 %	0.532	76 %	83 %	80 %
ResNet50V2	73.74 %	0.518	73.42 %	0.509	78 %	86 %	82 %
ResNet152V2	70.39 %	0.595	73.84 %	0.560	75 %	86 %	80 %
Xception	70.80 %	0.555	70.62 %	0.541	75%	88 %	81 %
VGG16	64.36 %	0.632	71.46 %	0.554	74 %	87 %	80 %
VGG19	65.50 %	0.609	68.67 %	0.579	72 %	89 %	79 %
GoogleNet	74.91 %	0.4991	76.08 %	0.501	82 %	80 %	81 %
Proposed approach using VGG19	**85.57 %**	**0.322**	**78.21 %**	**0.503**	**88.82 %**	**73.27%**	**80.30 %**
The proposed approach using GoogleNet	**80.07 %**	**0.431**	**81.28 %**	**0.451**	**90.78 %**	**76.29%**	**82.90 %**



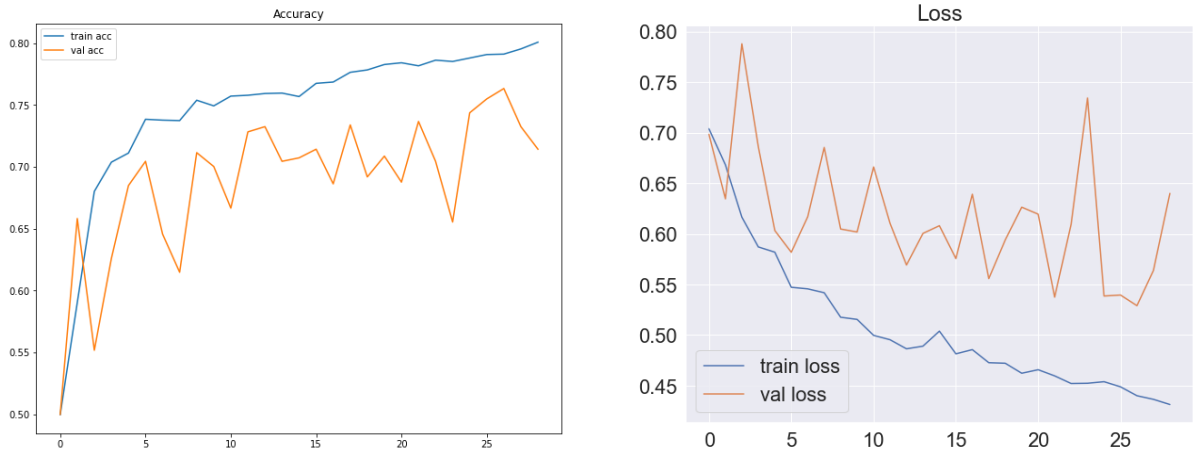
(a) (b)

FIGURE 6. Confusion Matrix Results for Classification: (a)VGG19 (b)GoogleNet



(a) (b)

FIGURE 7. Training and Validation Progress for VGG19 : (a)Accuracy progress (b)loss progress



(a) (b)

FIGURE 8. Training and Validation Progress for GoogleNet : (a)Accuracy progress (b)loss progress

Overall, deep learning shows much more efficient approaches for melanoma classification with less preprocessing required. Through working in the proposed approach, some enhancement processes can be made to increase accuracy, such as selecting better images with noise-free hair, selecting high-quality images, and merging machine learning methods with deep learning can increase the possibility of good results.

5. Conclusion

This paper proposes the melanoma skin cancer approach using deep neural networks. Melanoma skin cancer is one of the most dangerous cancers worldwide, with high numbers of deaths each year. The proposed approach works in binary classification with class 1 meaning Melanoma and class 0 meaning non_melanoma starting from a dataset used from ISIC 2019, data balance to increase generalization of the model, splitting of data into three sets (training 80%, validation 10%, testing 10%), followed by images resizing with fixed dimension 224x224 to be suitable for convolutional neural network architectures VGG19 and GoogleNet. Implementation of pre-trained VGG19 and GoogleNet and training using the first set and other sets to monitor model performance within the training process and after. Experimental results on the dataset show that VGG19 and GoogleNet achieve better results from the compared approach, with 85.57 % accuracy for VGG19 and 80.07 % accuracy for GoogleNet.

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