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Automated CAD for Melanoma (MM) skin Cancer using Machine Learning

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ABSTRACT

Skin cancer, particularly melanoma (MM), is a serious and potentially deadly disease in today's society. Early detection is crucial for effective treatment. Given the rapid progression of skin cancer, there is a pressing need for an automated CAD system to detect skin cancer in its early stages. However, one of the main challenges in developing such a system is extracting features from skin cancer images, as many visual characteristics of these images are similar. This research introduces an automated Computer-Aided Diagnosis (CAD) system for MM using transfer learning with the VGG16 model. The approach leverages a pre-trained VGG16 network to classify skin lesions into benign and MM categories. Utilizing a dataset from the International Skin Imaging Collaboration (ISIC), which includes images of various MM and benign stages, the proposed model demonstrated excellent training accuracy and promising validation results. The proposed CAD system can aid dermatologists in accurately analyzing MM skin cancer, saving time and enhancing patient treatment.

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Introduction

Lesion is an abnormal area of tissue or skin that has undergone some form of damage or disease. Lesions can appear as spots, bumps, sores, or other irregularities on the skin or within other organs. They can be benign or malignant, and their characteristics can vary widely depending on their type and location. Skin cancer is indeed a serious and common type of skin lesion. Detailed information about the different forms of skin cancer and related diagnostic advancements are:

1.1 Forms of Skin Cancer

Skin cancer can manifest in several forms, each with distinct characteristics and treatment approaches. The three most common types are:

1.1.1 Basal Cell Carcinoma (BCC):

- Development: BCC develops from the basal cells at the bottom of the epidermis, often in areas exposed to sunlight for prolonged periods.
- Appearance: It typically appears as a small, shiny, smooth, waxy, or pale lump. It may also present red patches with rough, dry, or scaly regions. Refer Figure 1.
- Growth Rate: BCC has a moderate growth rate, making it relatively easier to diagnose and treat if caught early.

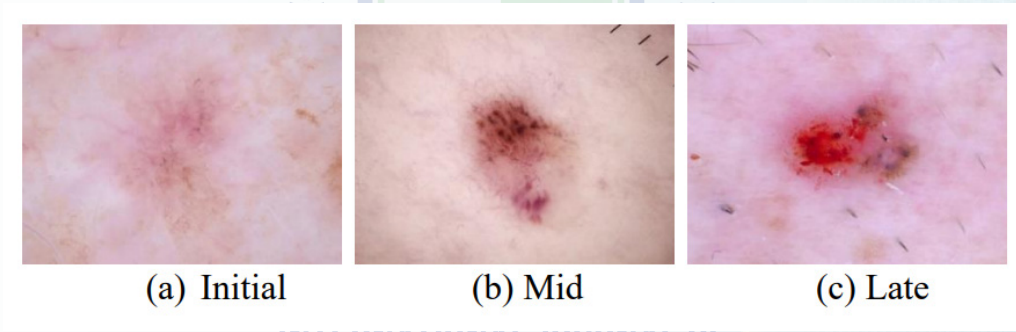


Figure 1. Initial, mid and late stages of BCC

1.1.2 Squamous Cell Carcinoma (SCC):

- Development: SCC originates in the squamous cells of the top layer of the skin.
- Spread: Unlike BCC, SCC can spread to other parts of the skin at an early stage, which is a key difference between the two.
- Appearance: SCC manifests as small, smooth lumps that may be brown in color. ReferFigure 2.

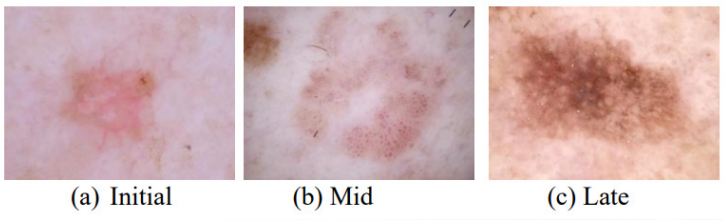


Figure 2. Initial, mid and late stages of SCC

1.1.3 Melanoma (MM):

- Development: MM is the most lethal form of skin cancer, developing in melanocytes, the cells responsible for producing pigment.

- Appearance: It is characterized by asymmetry in shape, uneven borders, and unnatural pigmentation. Early detection is crucial for effective treatment. Refer Figure 3.

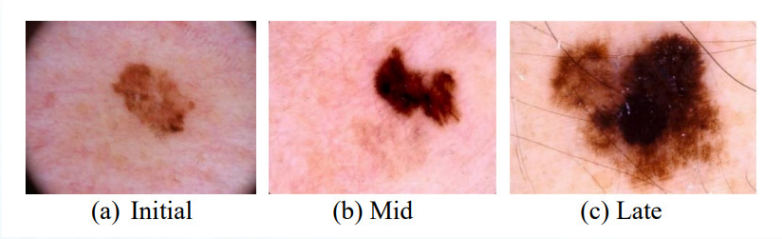


Figure 3. Initial, mid and late stages of MM

In the United States alone, there are 5.4 million new cases of skin cancer each year [1][2], and global figures are alarming [3][4]. Recent data indicates a 53% increase in new MM cases from 2008 to 2018 [2][5]. The death rate from skin cancer is expected to rise over the next decade, particularly for those diagnosed at a late stage. Late-stage detection results in a survival rate of less than 14% [6].

In contrast, early detection of skin cancer significantly improves the survival rate, which rises to over 97% [3]. This stark difference highlights the crucial need for timely diagnosis and intervention. Effective early detection strategies can dramatically enhance patient outcomes and reduce the overall impact of skin cancer. This research focus on MM skin cancer, as it is one of the most serious types of skin cancer due to its aggressive nature and potential to spread to other parts of the body. It originates in the melanocytes, the pigment-producing cells in the skin, and can quickly grow beyond the skin into nearby tissues and organs. If not detected and treated early, MM can spread to organs such as the liver, lungs, and brain, making it much more challenging to treat. Dermatologists use the ABCDE rule to assess skin lesions for MM. They check for Asymmetry (one half of the lesion not matching the other), Border irregularities (ragged or blurred edges), Color variation (multiple shades within the lesion), Diameter (lesions larger than 6 mm), and Evolving characteristics (changes in size, shape, or color over time). Despite its usefulness, the ABCDE rule has limitations. It can miss MM that doesn't fit the criteria, leading to false negatives, and may cause unnecessary anxiety and biopsies for benign lesions. The rule's subjective nature can result in inconsistent evaluations, and an emphasis on diameter might overlook smaller MM. Dermatologists use the ABCDE rule as a screening tool, complemented by other diagnostic methods and clinical expertise for a comprehensive evaluation. There is a need for automated computer aided diagnosis (CAD) for MM skin cancer.

1.2 Challenges in MM skin cancer detection

Detecting MM skin cancer presents several challenges:

1.2.1 Noise and Artefacts: Images of skin lesions can be obscured by unwanted elements such as blood vessels, hairs, and air bubbles, which interfere with accurate identification and analysis

1.2.2 Low Contrast: When the contrast between a lesion and the surrounding skin is low, it becomes difficult to effectively segment the lesion from its background, complicating diagnosis.

1.2.3 Size and Shape Variations: The wide range of lesion sizes, shapes, and locations adds complexity to image analysis. Accurate diagnosis often requires preprocessing to address these variations before applying diagnostic algorithms.

1.2.4 Color Lighting: Variations in skin lesion color, lighting, and reflections can alter dermoscopic images, resulting in inconsistencies and challenges in analyzing the images effectively.

1.2.5 Irregular Fuzzy Borders: Lesions with irregular and indistinct borders make it challenging to accurately define the edges of the lesion, which is crucial for precise asymmetry prediction and diagnosis [7].

2. Related work

Skin cancer can arise from a range of factors, including direct UV ray exposure and infections. To enable early detection of skin cancer, various techniques have been applied to images. These methods focus on identifying and analyzing visual patterns and abnormalities to ensure timely and accurate diagnosis. A thorough review has been conducted to assess these techniques for identifying skin cancer, providing researchers with insights to select the most effective approaches tailored to their specific requirements, refer Table 1 for summary.

[8] introduced a novel classifier using a decision forest approach for analyzing 173 dermoscopic images and generating a lesion severity score. This classifier exhibited a high sensitivity for melanoma detection, reaching up to 97.4%. However, the results were based on a relatively small dataset of dermoscopic images. Despite this limitation, the classifier showed considerable potential in accurately assessing lesion severity, suggesting its usefulness in skin cancer diagnosis. [9] proposed a transfer learning method for skin cancer detection, employing five advanced convolutional neural networks (CNNs) to develop both plain and hierarchical classifiers capable of distinguishing between seven types of moles from HAM10000 dataset. They enhanced model performance by using the DenseNet201 architecture and data augmentation techniques. This integration of transfer learning and sophisticated network models led to improved accuracy and effectiveness in skin cancer detection and classification. [10] Optimizing the hyperparameters of CNNs manually can be complex and time-consuming. To address this, authors proposed an Automated Hyper-parameter Optimized CNN that uses a Grey Wolf Optimization (GWO) algorithm for hyperparameter tuning. The model is applied to skin cancer classification and compared with CNNs optimized using Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) on ISIC dataset. The results show that the proposed model achieves a testing accuracy of up to 98.33%, which is about 4% higher than the PSO-based models and 1% higher than the GA-based models. Additionally, it has a testing loss of around 0.17%, which is 39.2% lower than the PSO models and 15% lower than the GA models.

[11] presented a classification method for human skin cancer using Deep Neural Networks (DNNs). Their experiments involved a diverse set of images and employed both three-way and nine-way classification approaches. Training the Convolutional Neural Networks (CNNs) with a substantial dataset of 129,450 clinical images yielded successful cancer detection, highlighting the efficacy of their method in skin cancer classification.

[12] presents an advanced diagnosis scheme for multi-class skin lesion classification. The approach combines a deep convolutional neural network (CNN) with an error-correcting output codes (ECOC) support vector machine (SVM). The scheme is designed to classify skin lesions into one of five categories: healthy, acne, eczema, benign, or malignant melanoma. The system was tested on a dataset of 9,144 images from various sources. AlexNET, a pre-trained CNN model, was employed to extract features, which were then classified using the ECOC SVM. The system achieved an overall accuracy of 86.21%, with 10-fold cross-validation employed to prevent overfitting. The results demonstrate that features extracted by the CNN significantly enhance the classification performance for different skin lesions.

[13] developed a deep learning U-Net architecture specifically for analyzing skin lesions. Their approach included tasks such as lesion segmentation, boundary distance map regression, and encoder functionality. By leveraging the U-Net architecture, their approach improved object localization and achieved pixel-wise classification, enhancing the accuracy of identifying the Region of Interest (ROI) in skin lesions.

Table 1. Summary of related work done by researchers for MM skin cancer detection

Reference	Images (Dataset)	Technique	Results
[8]	173 Dermoscopic images (limited dataset)	Decision forest classifier for dermoscopic images	High sensitivity for melanoma classification (up to 97.4%)
[9]	Images of seven types of moles (HAM10000 dataset)	Transfer learning with CNNs; DenseNet201	DenseNet201 is suitable for skin cancer detection
[10]	ISIC skin lesion multiclass dataset	Automated HyperParameter Optimized CNN with Gray Wolf Optimization	Achieved up to 98.33% accuracy
[11]	129,450 clinical images	Deep Neural Networks (DNNs) for skin cancer classification	Effective for skin cancer classification.
[12]	9,144 images from various sources	Hybrid approach: Deep CNN (AlexNET) + ECOC SVM classifier	Achieved an overall accuracy of 86.21%.
[13]	Images of skin lesions	Deep learning U-Net architecture for skin lesion analysis	Achieved Accuracy 87.61%

3. Transfer Learning

Transfer learning is a machine learning technique where a model developed for a particular task is reused as the starting point for a model on a different but related task. This approach leverages the knowledge gained from the initial task (often trained on a large dataset) to improve the learning efficiency and performance on the new task, especially when the new task has a smaller dataset. 3.1 Key Aspects of Transfer Learning:

The following aspects make transfer learning a highly effective approach in diverse fields such as computer vision, natural language processing, and medical diagnostics:

3.1.1 Pre-trained Models: These are models that have already been trained on large datasets and have learned general features that can be useful for other tasks. Common examples include models like ResNet, Inception, VGG Models and many more.

3.1.2 Feature Extraction: In this approach, the pre-trained model is used to extract features from the new dataset, which are then used to train a new model.

3.1.3 Fine-tuning: This involves taking a pre-trained model and slightly adjusting its parameters by continuing the training process on the new dataset. The pre-trained model's weights are typically adjusted very slowly (using a low learning rate) to preserve the learned features while adapting to the new task.

3.2 Benefits:

- Efficiency: It reduces the need for extensive computational resources and time required to train models from scratch.
- Performance: Improves model performance on tasks with limited data by leveraging the knowledge from related tasks with more abundant data.

- Practicality: Makes it feasible to develop high-performing models for niche applications with limited datasets.

4. Objectives of the proposed research work

- Data should be gathered from big, highly qualified approved centres.
- Data should be preprocessed to ensure that no vital data is lost.
- To propose an automated CAD MM skin cancer using transfer learning based VGG16.
- Train and test proposed deep architecture, end-to-end on skin cancer dataset, which comprises complete images of the early, medium, and late phases of infection status.

5. Methodology

This research aims to create an automated Computer-Aided Diagnosis (CAD) system for melanoma (MM) skin cancer by leveraging advanced imaging and machine learning algorithms to analyze skin lesions and aid dermatologists in diagnosing MM. We used transfer learning with the VGG16 deep architecture to accurately classify skin cancer images as either benign or malignant MM, improving diagnostic precision and efficiency.

5.1 Data Collection

Skin cancer dataset is collected from International Skin Imaging Collaboration (ISIC) [14], is a leading initiative focused on improving the diagnosis and treatment of skin cancer through the creation and dissemination of high-quality dermatological images. By providing a vast repository of annotated skin lesion images. Table 2 specifies the number of samples collected for MM and benign.

Table 2. Number of samples for each class in our dataset

Data Set	Melanoma (MM) Images	Benign Images
Train Set	438	360
Test Set	16	24

5.2 Oxford VGG

The Oxford VGG (Visual Geometry Group) model is a convolutional neural network that achieved notable success at the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014, securing second place in the image classification task and first place in the image localization task. Developed by a team of researchers from Oxford, the VGG model's weights and structure have been made publicly available. The model's architecture, as illustrated in Figure 4, consists of multiple 3x3 convolutional layers, 2x2 max pooling layers, and fully connected layers at the end. This straightforward yet effective design processes input images of 224x224x3 pixels (RGB format), making it a robust tool for image recognition tasks.

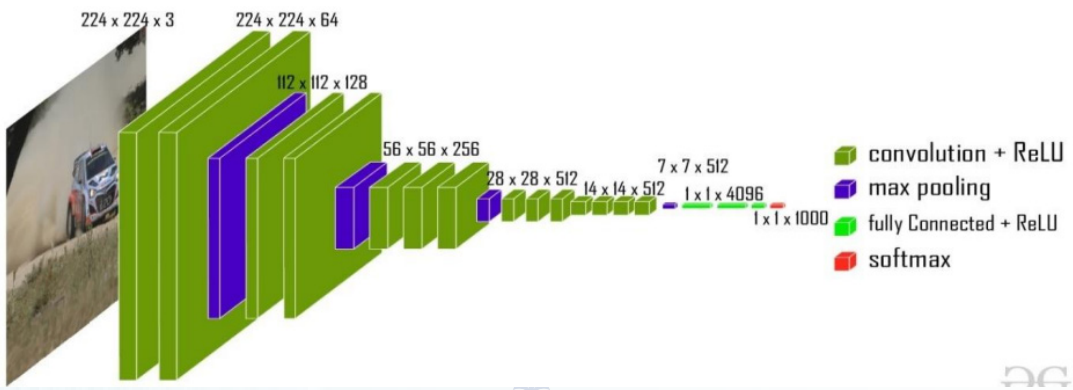


Figure 4. VGG16 Architecture (Image source: https://www.geeksforgeeks.org/vgg-16-cnnmodel/

5.3 Proposed model

The images in the dataset were all resized to 512x512 pixels, and the dataset includes benign and MM cases at various stages of infection. There were 798 images in train set, 40 images in test set, from the train set 20% of images that is 159 images are considered for validation set. For compilation, to calculate loss, binary_crossentropy and 'adam' optimizier were used.

The proposed model, as illustrated in Figure 5, leverages a pre-trained VGG16 architecture combined with a fully connected dense layer for binary classification. The model is structured as follows:

5.3.1 VGG16 Layer: Images are input into the VGG16 network, which includes pre-trained weights. These weights, obtained from training on a large dataset like ImageNet, are used to extract hierarchical features from the images. The output of the VGG16 model is a feature map that captures important patterns and structures. Mathematically, the output F of the VGG16 layer can be represented as:

$$F = VGG16 (X, WVGG16) \quad (1)$$

Here,

X : Input image WVGG16 : Pre-trained weights of the VGG16 model.

5.3.2 Dense Layer with Sigmoid Activation:

For a given input vector F (which is the feature map output from the VGG16 layer), the dense layer performs a linear transformation:

$$z = Wdense \ . F + bdense \quad (2)$$

Here,

Wdense : Weight matrix of the dense layer **F** : Input vector

bdense : Bias vector of the dense layer

z : Raw, unactivated output of the dense layer before applying the sigmoid function

The sigmoid activation function is then applied to z to obtain the final output ŷ which is a probability value between 0 and 1, which is used for binary classification:

$$\hat{y} = \sigma(\mathbf{z}) = \frac{1}{1 + e^{-\mathbf{z}}} \quad (3)$$

Here,

$\sigma(\mathbf{z})$: Sigmoid function applied element-wise to the vector $\mathbf{z}$,

e : Base of the natural logarithm.

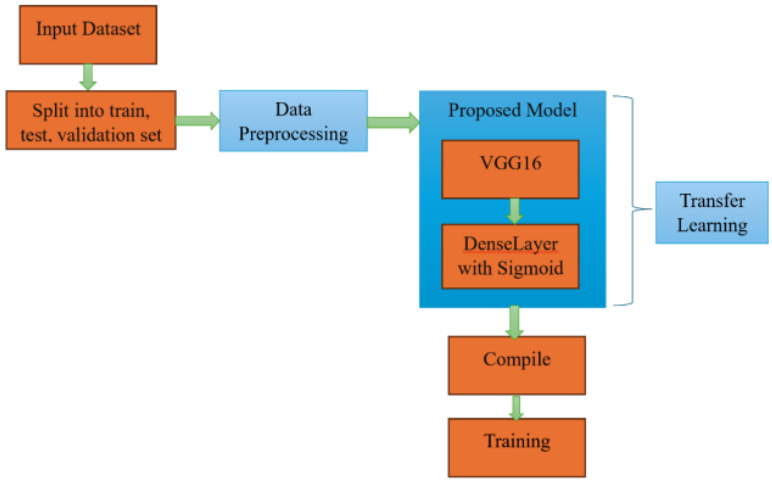


Figure 5. Proposed automated CAD for MM skin cancer

5.3.3 Loss Calculation: During model compilation, the binary cross-entropy loss function is used to measure the discrepancy between the predicted probabilities ŷ and the actual labels y. For a batch of N samples, the average loss is:

$$L_{\text{batch}} = \frac{1}{N} \sum_{i=1}^{N} - [y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)] \quad (4)$$

Optimizer (Adam): The Adam optimizer is used to adjust the model's weights during training, providing efficient optimization by combining the benefits of both gradient descent and adaptive learning rate methods.

5.3.4 Training parameters:

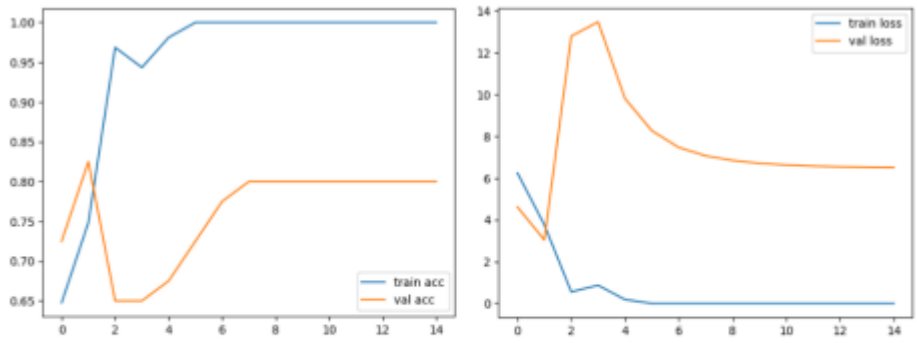
- Epochs: The model is trained for 15 epochs to ensure sufficient learning and convergence.
- Batch Size: A batch size of 32 is used, meaning the model processes 32 images at a time before updating weights.

The total number of iterations for weight updates is determined by the number of batches per epoch, calculated as:

$$\text{Number of Iterations} = \frac{\text{Total Training Samples}}{\text{Batch Size}} \quad (5)$$

6. Results

The experiment was carried out in google collab, and used a free GPU to train the model. VGG16 model has achieved 100% training accuracy, and validation accuracy is 80%. VGG16 correctly detects MM skin cancer at early, medium and final stage and also it detects benign cases. Results achieved by proposed model is shown in Figure 7.



(a) Accuracy (b) Loss

Figure 7. Results achieved by the proposed model

7. Conclusion and future work

The CAD system employing the VGG16 model successfully classifies skin lesions into benign and MM categories, achieving notable performance metrics. The model's high training accuracy and reasonable validation accuracy suggest its effectiveness in differentiating between MM and benign cases. The results underline the potential of using transfer learning to enhance MM detection capabilities. However, the validation accuracy indicates room for improvement, necessitating further optimization to ensure the model's robustness in real-world scenarios. Future work is to compare the results achieved by modified VGG16, with VGG19, ResNet50 and InceptionV3 and Detection models, and select which suits the best for early detection and CAD for MM skin cancer to support dermatologists.

References

Siegel R, Naishadham D, Jamal A. Cancer statistics, 2012. Cancer J. Clin. 2012: 10–29. https://doi.org/10.3322/caac.20138.

Esteva1 A, Kuprel1 B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S. Dermatologistlevel classification of skin cancer with deep neural networks. Nature 2017:115–26. https://doi.org/10.1038/nature21056.

Siegel R, Miller KD, Jamal A. Cancer statistics, 2018. Cancer J. Clin. 2018:7–30. https://doi.org/10.3322/caac.21442.

W. H. Organization. WHO. [link]. https://www.who.int/uv/faq/skincancer/en/in dex1.html.

Masood A, Al-Jumaily AA. Review article computer aided diagnostic support system for skin cancer: a review of techniques and algorithms. Int J Biomed Imaging 2013:1–22. https://doi.org/10.1155/2013/323268

Erkol B, Moss RH, Stanley RJ, Stoecker WV, Hvatum E. Automatic lesion boundary detection in dermoscopy images using gradient vector flow snakes. Skin Res Technol 2005:17–26.

Al-Masni MA, Al-antari MA, Choi M-T, Han S-M, Kim T-S (2018) Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks. Comput Methods Programs Biomed 162:221–231.

Ferris, Laura K., et al. "Computer-aided classification of melanocytic lesions using dermoscopic images." Journal of the American Academy of Dermatology 73.5 (2015): 769-776.

Thurnhofer-Hemsi, Karl, and Enrique Domínguez. "A convolutional neural network framework for accurate skin cancer detection." Neural Processing Letters 53.5 (2021): 3073-3093.

Mohakud, Rasmiranjan, and Rajashree Dash. "Designing a grey wolf optimization based hyper-parameter optimized convolutional neural network classifier for skin cancer detection." Journal of King Saud University-Computer and Information Sciences 34.8 (2022): 6280-6291.

Esteva, Andre, et al. "Dermatologist-level classification of skin cancer with deep neural networks." nature 542.7639 (2017): 115-118.

Hameed, N., A. M. Shabut, and M. A. Hossain. "Multi-class skin diseases classification using." 12th international conference on software. Knowledge, Information Management & Applications (SKIMA), IEEE. 2018.

Phan, Tran-Dac-Thinh, et al. "Skin lesion segmentation by u-net with adaptive skip connection and structural awareness." Applied sciences 11.10 (2021): 4528.

https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic/data [Accessed on: July 25, 2024]