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A Deep CNN Model for Skin Cancer Detection and Classification

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Abstract:

Skin cancer is one of the most dangerous forms of cancer when it is not detected early. If timely diagnosis and treatment are not provided, it can spread to other parts of the body, making it more difficult to treat. If early detection happens at that time, it plays a critical role in saving a life, as such an automated system for Skin lesion recognition has a highly valuable role in saving time and efforts, but also reducing the burden of the professional. This paper focus on using CNNs to classification skin cancer of 8 type and also provide difference between cancer skin and normal skin utilizing CNNs system processes the skin images to identify the various type and conditions including the a keratosis, bcc, dermatofibroma, meloma, nevus, pgk, scc, vascular lesion the deep learning model demonstrate a classification accuracy of 79.80%, model design with the multiple convolution layer, pooling layer, batch normalization, Adam optimization, max pooling layer, and output classification used SoftMax layer.

Keywords: Skin Lesion Classification, Deep Learning, CNN, Dermatoscopy, Data Augmentation, Intelligent Health Systems, ResNet50, Medical Image Analysis

1. Introduction:

Skin cancer is the most frequent type of cancer worldwide; melanoma is its lethal form. Early and timely detection is a critical point that can be treated and possibly cured. Melanoma causes 6,000+ deaths each year, and this number is growing all over the world[5]. The lesions of the skin look very similar; it is hard to distinguish benign from malignant ones, even for the experienced dermatologist. Quite often, there are limited resources, few specialists, and a lack of advanced equipment. Traditional biopsy methods were painful, slow, and expensive[1][2][3][4]. There exist eight main types: actinic keratosis, BCC or basal cell carcinoma, dermatofibroma, melanoma, nevus, PK or pigmented keratosis, SCC or squamous cell carcinoma, and vascular lesions. Deep learning, particularly CNNs, allows for the automated recognition and classification of skin cancer. The ability of CNNs to learn complex features from images can make them effective in the task at hand. This project will use CNNs to help facilitate skin cancer classification easily. The dermatology team will help the CNNs work faster and ensure more accurate diagnoses are predicted. In resource-constrained domains that face restricted processors, limited memory, restricted internet access, and limited budgets, this model aims to build a scalable solution that can handle workload increases without crashing or becoming too expensive. This project wants to identify these skin cancer types: actinic keratosis, BCC, dermatofibroma, melanoma, nevus, PK, SCC, and vascular lesions. Ultimately, the goal is to ensure skin cancer detection becomes more accessible, faster, and more reliable, improving patient outcomes through the reduction of deaths.

2. Literature Review:

Convolutional Neural Networks have been studied extensively for the identification of skin cancer. Several research works explore different techniques and models to enhance reliability and accuracy in CNNs.

In [1] proposed a deep learning approach for classifying skin cancer with VGG16 was proposed by utilising transfer learning. They pre-processed the images by mean and median filters to remove noise and then applied data

augmentation and normalisation. They used the VGG16 pre-trained frozen convolutional layers for feature extraction. They used a deep CNN, VGG16, for classification optimised by the Adam optimiser, and obtained an accuracy of 86.97%, a recall of 87.22%, and a precision of 86.92%. However, the study shows a big difference between accuracy in training and validation (99.62% vs. 84.97%), which is indicative of possible overfitting. The dataset was comprised of 3,297 ISIC images; again, these may not be representative of normal clinical testing

In [2] reviewed deep learning-based skin cancer detection methods were reviewed, considering 51 studies. Preprocessing steps used on the images included filtering out noise using a median or mean filter, making the levels of the image even using histogram equalisation, and hair removal. For the segmentation of the lesion from the rest, they used Otsu thresholding, geodesic active contours, and statistical region merging. Feature extraction using ABCD parameters, GLCM, 2-D wavelet transform, PCA, and pre-trained CNNs such as Alex Net, VGG16, and Res Net was carried out. For the classification stage, backpropagation neural networks, feed-forward neural networks, SVM, and deep CNNs-VGG-16, ResNet-152, Inception-v3, and DenseNet-201 were considered, while achieving an accuracy of about 70-98%. The datasets used for the said research work were ISIC (25,331 images), HAM10000 (10,015 images), PH2 (200 images), and Derm Quest, Derm IS, and Dermnet. Some challenges that need to be taken into account are high GPU requirements, small intra-class differences, imbalanced datasets, and a lack of representation of dark-skinned populations. There was also a great variation in lesion sizes, a limited number of age groups, and difficulty in having access to dermoscopic images.

In [3] proposed a deep CNN system was proposed for the detection and classification of skin cancer. This team used rotations, flips, rescaling, shading, translation, shearing, and resized images to 224×224 pixels as part of preprocessing. They did not perform any explicit image segmentation. They used a deep CNN for feature extraction with four convolutional blocks with 7×7 and 3×3 kernels, followed by batch Normalisation, ReLU, and max-pooling. For the classification part, they have added three dense layers having units of 256, 128, and 64 units consecutively, along with dropout of 25%, 25%, and 50%. They have trained it with the Adam optimiser, which uses categorical cross-entropy loss along with Softmax activation. The obtained accuracy is 95.98%. The original set contained 800 images, enhanced to 5,600 in the dataset across four classes: Actinic Keratosis, Basal Cell Carcinoma, Malignant Melanoma, and Squamous Cell Carcinoma. The split was 80% training and 20% testing. Challenges included overfitting due to similar visuals between classes, high computational cost, memory limits, and the small original dataset, which required strong augmentation.

In [4] proposed a CNN-based method was proposed for the classification of skin cancer in 2025. They have used image resizing, image normalisation, and data augmentation as part of preprocessing. Segmentation was performed implicitly. They have used many convolutional layers to get the spatial details with max-pooling and batch normalisation. For classification, they used a CNN with fully connected layers, SoftMax activation, and Adam optimiser. They were able to achieve 94% accuracy. The ISIC dataset consists of high-quality dermoscopic images, and the five classes are Melanoma, Dermatofibroma, Nevus pigmentosus, Squamous Cell Carcinoma, and Healthy Skin. Limitations include the fact that there is a lack of large and diverse datasets, models lack interpretability clinically for trust, biases exist regarding skin type classification, and overfitting needs to be prevented.

In [5] used a transfer learning approach was used with Google Net and VGG16 to classify skin cancer. They resized all images to 224×224 pixels and normalised them. No explicit segmentation was done. For feature extraction, they employed pre-trained Google Net (22 layers with inception modules) and VGG16 (16 layers, 3×3 filters, and five convolutional blocks) trained on ImageNet. For classifying, they used transfer learning with the Adam optimiser with a learning rate of 0.0001, trained for 25 epochs with a batch size of 128. Results showed that VGG16 recorded 99.62% training accuracy and 84.97% testing accuracy, while Google Net reached an accuracy of 88.81% in training and 80.54% in testing. There were 3,298 images in this dataset, out of which 1,800 were benign and 1,498 malignant. There was an 80/20 split between train/test data. These methods are very slow and take weeks even on NVIDIA GPUs, have very large model sizes, risk overfitting, and there is a big gap between the train and test accuracy of 14.65% for VGG16. Moreover, the dataset was limited.

In [6] presented a VGG16 transfer learning approach was presented for skin cancer classification. Preprocessing used mean/median filters, horizontal/vertical flipping, resizing to 224×224 pixels, and normalisation. No

segmentation was applied. Feature extraction employed frozen VGG16 convolutional layers (16 layers, 3×3 filters, five blocks with Max Pooling) pretrained on ImageNet. Classification used transfer learning with retrained fully connected layers, Adam optimiser (0.0001 learning rate), 25-30 epochs, batch size 32-128, achieving 99.62% training, 84.97% validation, 86.97% test accuracy. The ISIC dataset had 3,297 images (2,637 training, 660 testing) with manual labelling. Challenges included a significant training-validation gap (14.65%), indicating overfitting, a limited dataset size, visual similarity between lesions, a lack of distinguishing features, dataset imbalance, and the need for diverse datasets for clinical deployment.

In [7] presented a hybrid approach mixing deep learning with classical 6-DOF pose estimation for robotics. Preprocessing involved RGB-D image alignment using MS Kinect at VGA resolution. No explicit segmentation was used; RPN detected regions of interest. Feature extraction employed VGG16 (13 layers) for RPN, ResNet50 for classification with global average pooling, and SIFT features with 3D reprojection for pose estimation. Classification used two-stage detection: VGG16-based RPN (0.63 precision/0.98 recall) and ResNet50 classifier (0.99 precision/0.98 recall); cascade achieved 0.99 precision/0.92 recall; pose estimation used RanSaC and ICP refinement. The dataset had 30 images per object for 12 kitchen objects, with 10,000 synthetic images for RPN and 2,000 for classifier training. Challenges included low Kinect resolution producing sparse point clouds, non-real-time performance (1.9s total per image), a requirement for rich texture limiting applicability, and the need for scanned textures and geometric models for new objects.

In [8] presented a deep CNN with data augmentation was presented for skin lesion classification. Preprocessing used three augmentation types: geometric (cropping, flips), Colour Normalisation (pixels to -1.0 to 1.0 range), and warping (shearing, distorting, scaling). No segmentation was applied. Feature extraction employed pretrained Inception-V4 (trained on 1.28M ImageNet images) with Stem, four Inception-A, seven Inception-B, three Inception-C blocks, and average pooling, producing 1,539-dimensional features. Classification used three algorithms: Neural Network (two hidden layers, sigmoid, binary cross-entropy, RMSprop), achieving 89.2% AUC, 73.9% AP, 89.0% ACC; SVM (Linear SVC) 77.3-77.5% AUC; Random Forest 74.6-75.7% AUC. The dataset had 6,162 training images (1,114 melanoma, 5,048 non-melanoma) from ISIC 2017, ISIC Archive, PH2, with 600 testing images. Challenges included an imbalanced dataset (18.1% melanoma), scarcity of labelled data causing overfitting, average sensitivity (55.6%), and the detrimental effect of excessive augmentation on SVM/RF, with DAUG-100 performing worse than DAUG-50

In [9] presented an ensemble of deep neural networks was presented for skin lesion classification in the ISIC 2018 challenge. Preprocessing involved normalising images by subtracting ImageNet mean RGB values, converting pixel range to 0-1, and resizing to network input sizes. No segmentation was used. Feature extraction employed pretrained models (PNASNet-5-Large, InceptionResNetV2, SENet154, InceptionV4) as feature extractors with all layers frozen except the final FC layer. Classification used transfer learning with fine-tuning: 2 epochs with frozen weights (learning rate 0.0001), then 50 epochs with updated weights (learning rate 0.01); Adam optimiser, cross-entropy loss, Softmax for 7 classes, achieving PNASNet-5-Large: 0.76, SENet154: 0.74, Ensemble: 0.73 validation scores. The ISIC 2018 dataset had 10,015 training images (Melanoma: 1,113, Melanocytic nevus: 6,705, BCC: 514, others) with 193 validation images; HAM10000 was also used. Challenges included a highly imbalanced dataset, making generalisation difficult, limited training data (10k images) insufficient for training from scratch, high unstable gradient flow requiring careful fine-tuning, and overfitting risk.

In [10] presented a comprehensive review of medical image analysis using CNNs was presented. Preprocessing involved minimal operations as CNNs learn from raw pixels, with augmentation (random cropping, flipping, rotation, Colour jittering, intensity Normalisation). Segmentation methods included 3D multi-scale Otsu thresholding, kernel fuzzy clustering with level sets, and statistical shape-based features with hierarchical clustering. Feature extraction employed various CNN architectures (LeNet-5, VGG, Res Net, Inception, U-Net), learning hierarchical features through convolutional layers with max pooling; initial layers captured edges/blobs, higher layers focused on organ parts. Classification used fully connected layers with Softmax, SVMs, various optimisers, achieving body organ recognition: 92.23%, lung pattern: 85.5%, thyroid: 83%, breast cancer: 82.43%, Alzheimer's: 98.88%. Datasets varied: BRATS (brain tumor), ILD (lung), ADNI (Alzheimer's), and IRMA (radiographic), with thousands to millions of images. Challenges included the requirement for large labelled datasets and computational power, the

black box problem with unclear internal representations, scarcity of expert annotations, overfitting with small datasets, and difficulty in manual labelling.

In [11] presented a methodology for skin cancer detection using neural networks was presented. Preprocessing involved grayscale conversion, homomorphic filtering (FFT with Butterworth high pass filter) for illumination, median filtering for noise, bottom-hat filtering, erosion and dilation for hair removal. Segmentation used Otsu's global thresholding to minimise intra-class variance, followed by binarization and morphological hole-filling. Feature extraction applied the ABCD rule: asymmetry index (major/minor axes), compactness index ($\text{perimeter}^2/4\times\text{area}$), colour count (6 suspicious colours, 5% pixel threshold), and maximum diameter (longest perimeter distance). Classification employed a feedforward ANN with a single hidden layer (10 neurons) trained with Scaled Conjugate Gradient (60.9%), Levenberg-Marquardt (68.9%), and Bayesian Regularisation (76.9%, best). The dataset had 463 images from dermnet.com in 6 classes: Melanoma (100), BCC (97), SCC (36), Melanocytic Nevi (78), Seborrheic Keratoses (119), Acrochordon (33), with an 80/10/10 split. Challenges included complete misclassification of entire classes by SCG and LM, high intra-class variability with low inter-class variance, a small, imbalanced dataset, overfitting risk, and performance degradation on unseen images

In [12] presented an ensemble of deep neural networks was presented for skin lesion classification in the ISIC 2018 challenge. Preprocessing involved normalizing images by subtracting ImageNet mean RGB values, converting pixel range to 0-1, and resizing to network input sizes. No segmentation was used. Feature extraction employed pretrained models (PNASNet-5-Large, InceptionResNetV2, SENet154, InceptionV4) as feature extractors with all layers frozen except the final FC layer. Classification used transfer learning with fine-tuning: 2 epochs with frozen weights (learning rate 0.0001), then 50 epochs with updated weights (learning rate 0.01); Adam optimiser, cross-entropy loss, softmax for 7 classes, achieving PNASNet-5-Large: 0.76, SENet154: 0.74, Ensemble: 0.73 validation scores. The ISIC 2018 dataset had 10,015 training images (Melanoma: 1,113, Melanocytic nevus: 6,705, BCC: 514, others) with 193 validation images; HAM10000 was also used. Challenges included a highly imbalanced dataset, making generalisation difficult, limited training data (10k images) insufficient for training from scratch, high unstable gradient flow requiring careful fine-tuning, and overfitting risk

In [13], a method combining quantum computing and Inception-ResNet-V1 is proposed for multi-class skin damage classification. Preprocessing involved Min-Max normalisation (pixel values to), data augmentation (rotation, cutting, flipping) for minority classes, and weighted random sampling to prevent overfitting. No segmentation was used. Feature extraction employed an improved quantum Inception-ResNet-V1 with FC layer removed; quantum convolutional layers used parameterised quantum filters (CNOT gate, rotation gate Rx) for quantum state encoding, converting pixels to quantum states via rotation gates; average pooling as final layer. Classification used SVM replacing FC layer, batch size 10, 32 epochs, learning rate 0.001, achieving 98.76% accuracy, 98.26% precision, 98.4% sensitivity, 99.81% specificity. The ISIC 2019 dataset had 25,331 images in 8 classes: NV (12,875), MEL (4,522), BCC (3,323), BKL (2,624), AKIEC (867), SCC (628), DF (239), VASC (253) with 80/10/10 split; minority classes augmented. Challenges included a highly imbalanced dataset (NV 50× VASC) causing bias, overfitting from repeated samples, large computational requirements, and accuracy degradation without weighted sampling (95.05% vs 98.76%

3. **Methodology :**

3.1 Dataset :

Image datasets are one of the most extensively utilised public resources in developing an automatic skin cancer classification system. It contains high-quality pictures of skin cancer been used as a benchmark for the training and testing of deep learning models on the classification of skin cancer.

The dataset includes images categorised into 8different classes:1) a karatosis, 2)bcc, 3) dermatofibroma, 4) melanoma, 5) nevus, 6) pgk, 7) scc, 8) vascular lesion

Figure 1: Sample image of skin cancer

3.2 proposed model :

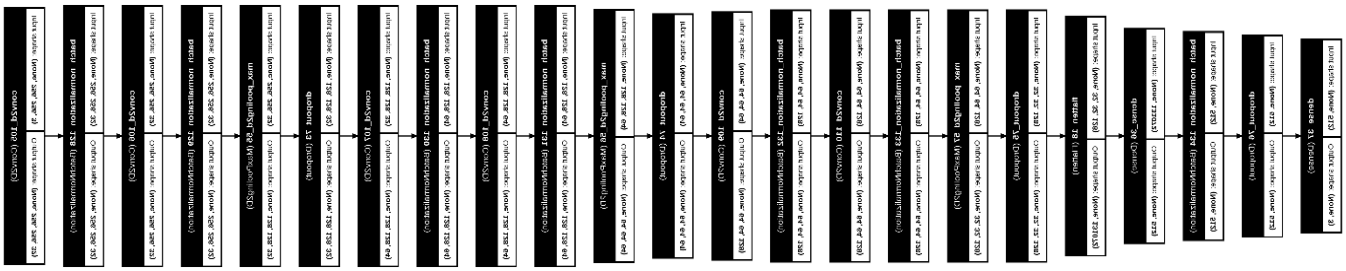

Figure 2: image of our proposed model

This is a deep convolutional neural network designed for image classification. It takes input images of size 256×256×3 (RGB) and passes them through layers of convolution, normalisation, pooling, and dropout. While processing the image, its size diminishes as the network learning more and more complex features.

It consists of a standard architecture with an encoder-decoder structure, divided into three major blocks. Each block is composed of two Conv2D layers, with subsequent batch normalisation and max pooling, and a dropout to prevent overfitting. This results in an image size reduction, from 256×256 to 128×128, then to 64×64, and finally to 32×32, while the number of feature channels increases from 32 to 64 and finally to 128. Key components of the model include convolution layers, batch normalisation, pooling, regularizers, dense layers, and the final output

4. Result :

In this section, we describe our implementation details. Our utilised data set is a collection of automobile images obtained from Kaggle. We found and categorised these images using a state-of-the-art deep learning model architecture called CNN. The data set trained the CNN in an end-to-end manner. A separate training, validation, and testing dataset was used to evaluate performance. Information for the CNN model will be documented in the next subsections, and the contribution of each model will be presented in the classification process section for the CNN model.

(original dataset) :

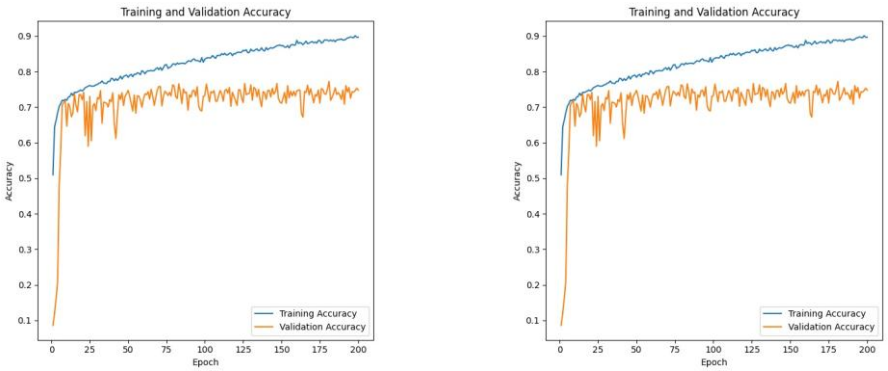

Figure 3: (a) Accuracy, and (b) Loss Graph of our proposed model.

The convolutional neural network (CNN) created a solid foundational model to classify skin cancer due to its fairly good feature extraction capabilities from dermoscopic images, and it performed relatively stable across classes. It achieved its best training accuracy of 90.59% and best validation accuracy of 79.80%, indicating good learning and moderate generalisation for unseen samples. Precision and recall produced balanced curves, and the F1-score indicated the CNN performed strongly and consistently for sharply defined lesions, while failure to detect lesions occurred for visually indeterminate and low-contrast detections. Overall, while a CNN provides support of a reasonable and stable model with which to refer and performed fairly well, its parameterisation of the model and limited inductive bias towards dermatologic texture may also limit scalability and generalisation across clinical workflows in practice. Therefore, despite overall stability and providing a fair method to benchmark/validate, further development of the CNN to improve clinical robustness of models would best use augmentation of data, classbalancing/rebalancing, and tuning using regularisation, ensembling or attention variants towards improvement.

(marge image):

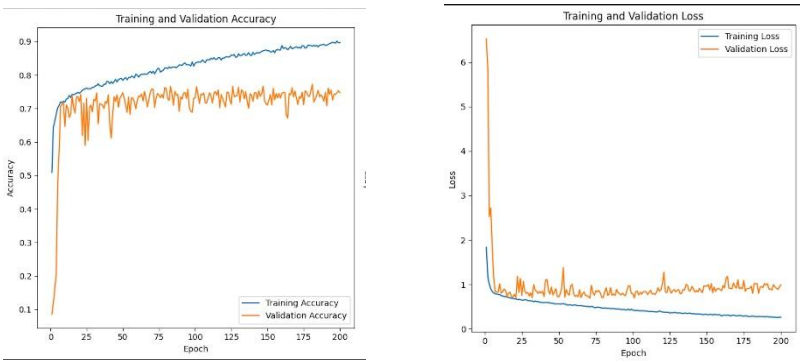

Figure 4: (a) Accuracy, and (b) Loss Graph of our proposed model.

A convolutional neural network (CNN) provided a sturdy baseline for skin cancer classification, having strong capabilities for feature extraction and consistent performance across all classes of lesions. The model achieved a maximum training accuracy of 83.82% and a validation accuracy of 75%, which indicated moderate generalisation to unseen examples after training. Both precision and recall exhibited a balanced profile, and the F1-score demonstrated consistent detection of well-defined lesions, but was challenged by visually ambiguous or low-contrast lesions. While the indicator of CNN performance established a stable baseline, the inductive bias and parameterisation (akin to other deep learning models) of a conventional CNN may stymie effective clinical scalability and generalisation in real-world workflows within dermatology. Overall, the CNN provides a reliable baseline and practical framework for advancing clinical care with augmentations of data, rebalancing of class distribution, and fine-tuning through regularisation, ensembling, and even attention-based models.

5. CONCLUSION :

This research project utilised a deep convolutional neural network (CNN) to classify skin cancers into eight lesion categories using three datasets. The researchers recorded the greatest accuracy from the original dataset with a training accuracy of 90.59% and a validation accuracy of 79.80%. Overall, the neural network was three layers deep and included batch normalisation, dropout, and data augmentation. The authors built the model in TensorFlow/Keras using Google Colab, with the Adam optimiser and the use of sparse categorical cross-entropy loss. The model provided confident feature extraction for well-characterised lesions; however, it performed poorly under the condition of visually similar cases and class imbalance. Suggested next steps for the authors were to incorporate transfer learning with pre-trained models, utilise attention mechanisms, aggregate during training via ensembles, and use resampling or a weighted loss function when correcting for class imbalance to improve clinical potential.

REFERENCES :

[1] Mahmud, Tanvir, and S A Sabbirul Mohosin Naim."Skin Cancer Classification Using VGG-16."International Journal of Innovative Science and Research Technology, vol. 10, no. 7, July 2025, pp. 457-463.DOI: 10.38124/ijisrt/25jul139

[2] Dildar, Mehwish, Shumaila Akram, Muhammad Irfan, Hikmat Ullah Khan, Muhammad Ramzan, AbdurRehman Mahmood, Soliman Ayed Alsaiari, Abdul Hakeem M Saeed, Mohammed Olaythah Alraddadi, and Mater Hussen Mahnashi."Skin Cancer Detection: A Review Using Deep Learning Techniques."International Journal of Environmental Research and Public Health, vol. 18, no. 10, May 2021, pp. 5479.DOI: 10.3390/ijerph18105479Reddy,

[3] 3.Junayed,MasumShah,NipaAnjum,AbuNomanMdSakib,andMdBaharulIslam."ADeepCNNModelforSkinCancerDetectionandClassification."ComputerScienceResearchNotes,vol.3101,January2021,pp.7180.DOI:10.24132/CSRN.2021.3002.8

[4] Reddirouthu, Manusree, Manga Akhila, and S. Vijaya Lakshmi."Skin Cancer Classification Using CNN."International Journal for Multidisciplinary Research, vol. 7, no. 3, May-June 2025, pp. 1-8. DOI:10.IJFMR250343814J

[5] Ummapure, Suryakanth B., Ravindrakumar Tilekar, and Satishkumar Mallappa."Skin Cancer Classification using VGG-16 and Googlenet CNN Models." International Journal of Computer Applications, vol. 184, no. 42, January 2023, pp. 5-9. DOI: 10.5120/ijca2023922497

[6] Mahmud, Tanvir, and S A Sabbirul Mohosin Naim."Skin Cancer Classification Using VGG16."International Journal of Innovative Science and Research Technology, vol. 10, no. 7, July 2025, pp. 457-463.DOI: 10.38124/ijisrt/25jul139

[7] Stefanczyk, M. and Bochenski, T., 2020. Mix-ing deep learning with classical vision for object recognition Journal of WSCG, Vol.. 28, No.1-2, 2020.

[8] Pham, T.C., Luong, C.M., Visani, M. and Hoang, V.D., 2018, March. Deep CNN and data augmentation skin lesion classification. In Asian Conference on Intelligent Information and Database Systems (pp.573-582). Springer, Cham

[9] Mohamed, E.H. and El-Behaidy, W.H., 2019, December. Enhanced Skin Lesions Classification Using Deep Convolutional Networks. In 2019, Ninth International Conference on Intelligent Computing and Information Systems (ICICIS) (pp. 180-188). IEEE.

[10] Anwar, S.M., Majid, M., Qayyum, A., Awais, M., Alnowami, M. and Khan, M.K., 2018. Medical image analysis using convolutional neural networks: a review. Journal of medical systems, 42(11), pp.1-13

[11] Victor, A. and Ghalib, M., 2017. Automatic detection and classification of skin cancer. InternationalJournal of Intelligent Engineering and Systems, 10(3), pp.444-451.

[12] Milton, M.A.A., 2019. Automated skin lesion classification using an ensemble of deep neural networks in ISIC 2018: Skin lesion analysis towards melanoma detection challenge. arXiv preprintar Xiv:1901.10802

[13] Li, Z. et al. A classification method for multiclass skin damage images combining quantum computing and InceptionResNetV1.Front.Phys.10,1120. https://doi.org/10.3389/fphy.2022.1046314 (2022).