Volume 70, Issue 1, 2026

Journal of Scientific Research

of

The Banaras Hindu University

SKIN VISION: Skin Cancer Detection Using CNN & Vision Transformer

Shahana Shani AT[1], Swapna Mol George[2]

[1]PG and Research Department of Computer Science, Sullamussalam Science College, Areekode, Affiliated to University of Calicut, Kerala, India, Shahanashaniat8@gmail.com

[2] Assistant Professor, PG and Research Department of Computer Science, Sullamussalam Science College, Areekode, Affiliated to University of Calicut, Kerala, India, smgjaison@gmail.com

Abstract: **Skin cancer continues to be a significant global health concern, with its incidence rates increasing alarmingly. The early and timely detection of the disease is crucial; it helps patients recover from the disease and improves their health. Machine learning has proven to be a valuable asset in this field. In our research, we assessed the performance of three algorithms, CNN, Vision Transformer (ViT), and a Combined model of CNN and ViT, on two datasets DermIS and skin cancer ISIC datasets: one for binary classification and another with nine classes vascular lesion, squamous cell carcinoma, seborrheic keratosis, pigmented benign keratosis, nevus, melanoma, dermatofibroma, basal cell carcinoma, and actinic keratosis. The combined model consistently excelled, achieving an accuracy of 97.78% on the DermIS dataset and an accuracy of 98.89% on the skin cancer ISIC dataset. These outcomes suggest that the integrated model surpasses the individual models, Achieving higher accuracy than the state-of-the-art results from the datasets. These findings illustrate the robustness and potential of our system, which outperformed baseline models, demonstrating its versatility and applicability in real-world skin cancer detection scenarios.**

Index Terms: **CNN, ViT, Vision Transformer, Skin cancer Detection, Malignant, Dermoscopic.**

I. INTRODUCTION

The skin, being the largest organ, is highly susceptible to cancer, with melanoma and non-melanoma skin cancers as the primary types. Skin cancer rates are rising globally, making timely detection crucial for effective treatment. Melanoma, though less common, is particularly deadly, accounting for only about 1% of cases but with high mortality rates (Dildar et al., 2021), while non-melanoma skin cancers often require painful treatments and are challenging to monitor due to unreliable registration systems. Melanoma arises from the uncontrolled growth of melanocytes, and its incidence has increased by 4% annually in the U.S. since the 1970s (Jemal et al., 2001).

Genetic factors, personal characteristics, and UV exposure increase melanoma risk, necessitating improved detection methods beyond traditional self-exams. Multiple datasets are available for skin cancer detection, each utilized in various studies. The DermQuest dataset (Boer & Nischal, 2007), redirected to Derm101 in 2018 and deactivated by 2019, included 22,082 dermoscopic images. AtlasDerm (Argenziano et al., 2000) offers training illustrations, while Dermnet (Dermnet, n.d.) contains over 23,000 images of 643 skin diseases. Dermofit has 1300 images in ten categories. In this study, we used the ISIC (ISIC Archive, n.d.) dataset, which contains eight classes of malignant skin cancers, and the DermIS (DermIS, n.d.) dataset, which categorizes lesions as either malignant or benign. Parameters such as symmetry, color, size, and shape of skin lesions help to differentiate between benign conditions and life-threatening melanomas.

Recent advancements in skin cancer detection leverage machine learning, deep learning, and image processing algorithms. Techniques like artificial neural networks (ANN) (Kanimozhi & Murthi, 2016), convolutional neural networks (CNN) (Zhang et al., 2020), and k-nearest neighbors (KNN) (Sajid & Rajesh, 2018) are prominently used. CNNs, known for their high accuracy and detection speed (Albahar, 2019; Hosny et al., 2019; Khan et al., 2020), excel in extracting spatial features and fine-grained details. Vision Transformers (Aladhadh et al., 2022) capture long-range dependencies and global context, aiding in understanding skin lesion patterns. Our study combined CNNs with Vision Transformers to analyze skin lesion images.

By integrating CNNs for local feature extraction with Vision Transformers for global context, our model effectively analyzes skin lesion images, identifies primary features related to skin cancer, and makes precise predictions. This hybrid approach utilizes both architectures' strengths, resulting in a reliable and accurate early skin cancer detection system to aid healthcare professionals. The contributions of this work include detecting skin cancer using CNN with the DermIS and ISIC datasets, utilizing Vision Transformers for skin cancer detection with the same datasets, employing a combined model of CNN and Vision Transformers for improved accuracy, determining whether skin cancer is malignant or benign, and identifying the specific type of cancer from nine different classes. The organization of the

DOI: 10.37398/JSR.2026.700105

remaining sections of the paper is as follows: section 2 provides existing works in the literature; Section 3 outlines the methodology adopted in the paper; Section 4 contains the result section with the inferences made by the experiments; and Section 5 concludes with a discussion of future work.

II. LITERATURE REVIEW

This section reviews research articles belonging to deep learning, machine learning, and multi-model imaging in the context of skin cancer detection. Researchers analyze lesions' symmetry, color, size, and shape to differentiate between benign and malignant melanomas. Standard methods for feature extraction include GLCM and the ABCDE Rule. A prevalent approach for melanoma detection is the ABCDE rule (Nachbar et al., 1994), which stands for asymmetry, borders, color, diameter, and evolving. Figure 1 shows the rules of the ABCDE algorithm. These criteria are warning signs for diagnosing melanoma, with high asymmetry or irregular borders being initial indicators (Giotis et al., 2015), wherein asymmetry is calculated by dividing the total area of the segmented image into two halves (Aladhadh et al., 2022). While the ABCDE method is standard, our work diverges by employing deep learning techniques instead of relying on the GLCM or the ABCDE rule. The literature highlights a shift from traditional methods to advanced machine-learning techniques for diagnosing malignant melanoma. Traditional approaches often fall short, prompting the development of Computer-Aided Diagnosis (CADx) systems using dermatoscopy images and machine-learning algorithms like SVMs and CNNs.

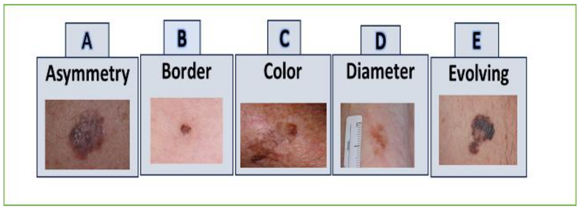

Fig 1: Traditional clinical analysis ABCDE rule

Dildar et al. (2021) and Pacheco and Krohling (2019) describes the most recent developments in skin cancer detection and names the limitations as CAD systems, clinical, dermoscopic, and histological pictures. As demonstrated in various studies, SVM is effective in skin cancer detection. Murugan et al. (2019) employed the GLCM, ABCD rule, Random Forest, Support Vector Machine (SVM), and kNN (k Nearest Neighbor) classifiers. Moreover, the SVM classifier yielded better results for the classification of skin lesions, as in (Doukas et al., 2012), with an accuracy of 77.06 %. Xie et al. (2016) showcased highly accurate systems, with SVM and ensemble NN models yielding impressive results of a1.11%. Masood et al. (2014) Introduced an automated skin cancer diagnostic system, evaluating the performance of three ANN learning algorithms: Levenberg–Marquardt (LM), resilient backpropagation (RP), and scaled conjugate gradient (SCG). Their study found that the LM algorithm achieved the highest specificity score of 95.1%, while the SCG algorithm achieved a sensitivity score of 92.6%. They also proposed a mole classification system based on the ABCD rule, achieving a 97.51% accuracy rate. Aswin et al. presented a novel method for skin cancer detection using genetic algorithm (GA) and ANN algorithms (Aswin et al., 2014). Their approach involved preprocessing images for hair removal, extracting the region of interest (ROI) using the Otsu thresholding method, and employing a hybrid ANN and GA classifier to classify lesion images into cancerous and noncancerous classes, achieving an accuracy of 88%. Ain et al. (2023) developed a hybrid federated learning method combining CNN and SVM for diagnosing melanoma. They used the ABCD rule for lesion segmentation and malignancy classification. The proposed Async-Fed-CNN-SVM achieved superior performance compared to random forest and KNN, demonstrating increased robustness with a 92% accuracy rate. Dildar et al. (2021) investigates various neural network techniques for detecting and classifying skin cancer, such as ANNs, CNNs, KNNs, and RBFNs. Among these, CNNs stand out as they excel in processing medical images through their advanced computer vision capabilities.

III. METHEDOLOGY

In this work, we implemented three models for skin cancer detection using two popular datasets, DermIS (Dermatology Information System) and ISIC, as shown in Figure 2. CNNs excel in image processing tasks, particularly in local feature extraction, which is crucial for analyzing skin lesion images. Conversely, despite their strength in understanding the global context, Vision Transformers (ViTs) have been limitedly used in skin cancer detection. ViTs can capture broader patterns in lesions, complementing CNNs' local analysis. This work focused on CNN and Vision Transformer models. We integrated both architectures, utilizing CNNs as the primary feature extractor to capture local details and then feeding the output to ViTs for comprehensive global analysis. This hybrid approach aims to leverage the strengths of both CNNs and ViTs for enhanced skin cancer detection accuracy.

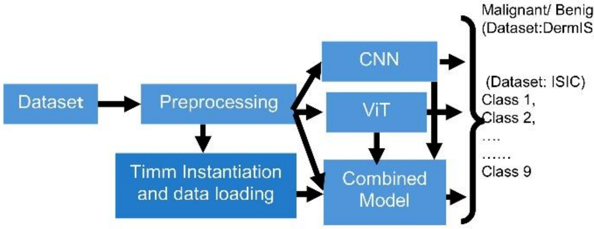

Fig. 2: Architecture of the proposed Experiment.

A. Datasets

We utilized DermIS (Dermatology Information System) and Kaggle's Skin Cancer ISIC datasets (Kaggle Skin Cancer ISIC, n.d.). The DermIS dataset, a collaboration between two universities, includes 6588 images partitioned into dermatology and paediatric dermatology sections (DermIS, n.d.). Figures 3 and 4 show samples from the DermIS and ISIC datasets, respectively.

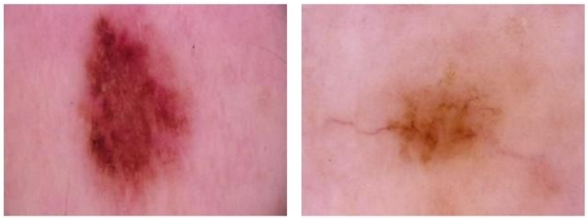

Fig. 3: Sample images from DermIS (a. malignant, b. benign)

Fig. 4: Sample image of ISIC dataset with dermoscopic images of nine classes. (vascular lesion, squamous cell carcinoma, seborrheic keratosis, pigmented benign keratosis, nevus, melanoma, dermatofibroma, basal cell carcinoma, and actinic keratosis)

The DermIS dataset classifies skin lesions into two classes: malignant and benign. The ISIC archive, introduced at the ISBI Challenge 2016, contains skin lesion datasets released by the International Skin Imaging Collaboration (ISIC Archive, n.d.). We used only 2239 training and 118 testing images, categorized into malignant melanomas and benign nevi classes. The ISIC dataset consists of nine classes, including vascular lesion (139 images), squamous cell carcinoma (181 images), seborrheic keratosis (77 images), pigmented benign keratosis (462 images), nevus (357 images), melanoma (438 images), dermatofibroma (95 samples), basal cell carcinoma (376 images), and actinic keratosis (114 images) as indicated in Figure 5. ISIC continually expands, promoting automated systems for skin cancer diagnosis

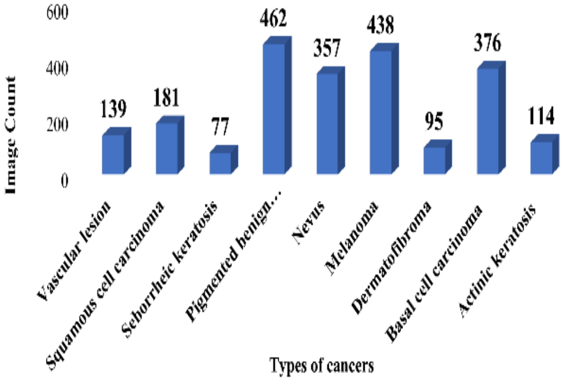

Fig. 5: Train samples from ISIC dataset without augmentation

B. *Preprocessing*

The preprocessing pipelines for CNN and Vision Transformer (ViT) models share common steps but differ. For CNN preprocessing, images were loaded in, resized to 48x48 pixels using OpenCV, and converted into NumPy arrays for computational efficiency. Normalized Pixel values to a [0, 1] range by dividing by 255 to enhance model performance, and the train test split was on a ratio of 80:20. Images were reshaped to (48, 48, 1) to fit the CNN's input requirements, performed data augmentation using Kera's' ImageDataGenerator with transformations like rotation, zoom, and flipping to increase dataset diversity and mitigate overfitting.

In ViT preprocessing, images were initially loaded in RGB format, resized to 224x224 pixels, and converted into PyTorch tensors. Subsequently, the images were normalized using mean and standard deviation values from the ImageNet dataset. The data was then fed into a Data Loader with a batch size of 32, where the training data was shuffled, but the validation set remained sequential for evaluation purposes. The key differences between the CNN and the ViT models include image resizing, color processing from grayscale to RGB, and specific reshaping needs for CNN.

The preprocessing for the combined model includes handling both CNN and Vision Transformer (ViT) components. The ViT model was initialized through the timm library with the ViT-Base model, featuring a 16-pixel patch size and 224x224 input dimensions, pre-trained on ImageNet, and customized to match the dataset's number of classes. For the CNN, images were resized to 48x48 pixels and converted to NumPy arrays. Both models utilized Cross Entropy Loss for multi-class classification and the Adam optimizer with a 0.0001 learning rate for training. The dataset was split into 80-20 for training and testing, with a batch size of 32. Images were standardized during preprocessing to ensure consistency, and the model was trained over 28 epochs to facilitate sufficient learning for both components.

C. *CNN*

Convolutional Neural Networks (CNNs) process input images of skin lesions through multiple convolutional and pooling layers to identify patterns and reduce dimensionality. Fully connected layers then interpret these feature maps to classify the lesions as benign or malignant, allowing CNNs to diagnose skin cancer with high accuracy autonomously.

The proposed convolutional neural network (CNN) architecture includes multiple layers: an initial Conv2D with 64 filters of 5x5 dimensions using ReLU activation, followed by MaxPooling2D to downsample feature maps. Additional Conv2D layers with 64 and 128 filters of 3x3 dimensions enhance feature extraction, while AveragePooling2D layers smooth and reduce dimensionality. The output is then flattened and passed through two fully connected Dense layers with 1024 neurons each and ReLU activation, interspersed with Dropout layers to prevent overfitting, concluding with a Dense layer using softmax for multi-class classification.

D. *Vision Transformer*

To transform input images into token representations, Vision Transformers (ViTs) divide them into smaller, fixed-sized patches. Positional encodings are added to these tokens to preserve spatial information about their original locations within the image. Multiple layers of transformer encoders help process the token embeddings. Using self-attention mechanisms allows each token to integrate information from others, capturing the global context necessary for classification and segmentation.

In particular, Vision Transformers (ViTs) use feedforward neural networks within each transformer layer to conduct non-linear transformations and extract significant features from token embeddings. Generates predictions from the learned features through a classification head by feeding output token representations, allowing the ViT to excel in tasks such as image classification and object detection. ViTs present a promising method for skin cancer detection by potentially identifying complex patterns in skin lesion images, thus aiding in accurate diagnoses. This study utilizes timm to initialize a Vision Transformer (ViT) model with pre-trained weights for skin cancer classification.

E. Combined Model (CNN and Vision Transformer

The integrated model demonstrates remarkable adaptability with CNNs' and Vision Transformers' unique architectures and learning methods. CNNs focus on local image regions, whereas Vision Transformers treat the entire image as tokens. This alliance allows the model to handle various skin lesion images by capturing both local details and global context, thus improving its capacity to differentiate between benign and malignant lesions.

Timm instantiated a Vision Transformer (ViT) model in this study using pre-trained weights for skin cancer classification. The Timm create model function allows users to quickly generate and modify models by specifying parameters like model architecture, pre-trained weights, and the number of output classes. Initially, a CNN extracted image features, which were then passed to the ViT and treated as a sequence of patches; ViT used self-attention mechanisms to model the relationships among these patches, capturing global context and improving classification accuracy. We trained the model using cross-entropy loss and the Adam optimizer, with evaluation metrics including loss and accuracy to assess the results.

IV. RESULT

Performance measures, such as F1-Score, Precision, and sensitivity, were calculated alongside accuracy and loss to evaluate the models' performance using equations 1 to 4, which provide a transparent and systematic approach to model evaluation.

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

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

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

$$F1-score = \frac{2*Precision*Sensitivity}{Precision+Sensitivity} \quad (4)$$

Tables 1 and 2 display the experimental results from our study. Specifically, Table 1 presents outcomes using the DermIS dataset, focusing on classifying cancer as malignant or benign. The CNN model achieved an accuracy of 93%, with precision, sensitivity, and F1-scores at 95%.

The Vision Transformer (ViT) reached an accuracy of 90% but obtained perfect precision, sensitivity, and F1-scores of 100%. The combined model outperformed the others with an accuracy of 97.48%. These findings highlight the superior performance of our integrated model compared to previous studies such as (Khan et al., 2019), which reported an accuracy, sensitivity, specificity, and precision of 96%, 97%, 96%, and 97%, respectively, using SVM, Gaussian filter, and K-means clustering for segmentation.

Table I: Results from DermIS Dataset

Model	Accuracy %	Precision %	Sensitivity%	F1-score %
CNN	94	97	96	96
ViT	92	100	100	100
Combined model	**98.89**	**100**	**100**	**100**

In the case of the ISIC dataset, the results of the CNN, Vision Transformer (ViT), and the combined model on the image classification, we observed notable differences in performance between the individual models and their combination as shown in Table 2.

Table II: Results from ISIC Dataset

Model	**Accuracy %**	**Precision %**	**Sensitivity %**	**F1-score %**
CNN	93	95	95	95
ViT	90	100	100	100
Combined Model	**97.48**	**100**	**100**	**100**

CNN, this model achieves a substantial accuracy of 94%, with precision at 97% and sensitivity and F1-scores at 96%. Vision Transformer (ViT) exhibits slightly lower accuracy at 92% but perfect precision, sensitivity, and F1-scores of 100%. The combined model achieves the highest performance across all metrics, with an impressive accuracy of 98.89% and perfect precision, recall, and F1-scores of 100%. These findings indicate that, despite the robust performance exhibited by the CNN model, both the ViT and the integrated models showcase superior proficiency in attaining impeccable classification outcomes based on the F1 score. Figure 6 shows the combined model's training loss and validation loss, as well as the training accuracy and validation accuracy plot on the ISIC dataset.

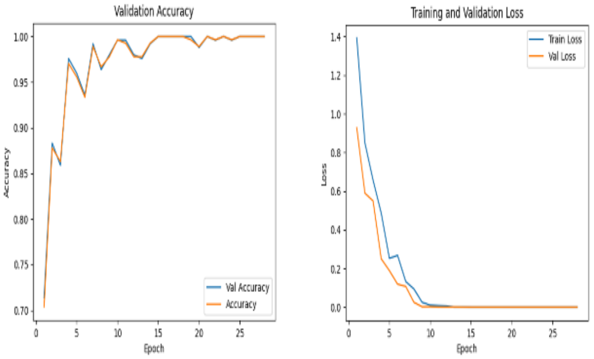

Fig.6: combined model's training loss and validation loss, the training accuracy and validation accuracy plot on the ISIC dataset

In comparing the performance of CNN, Vision Transformer (ViT), and the combined model on two datasets, DermIS and ISIC, key differences emerge in how each model responds to the distinct datasets, as indicated in Figure 7.

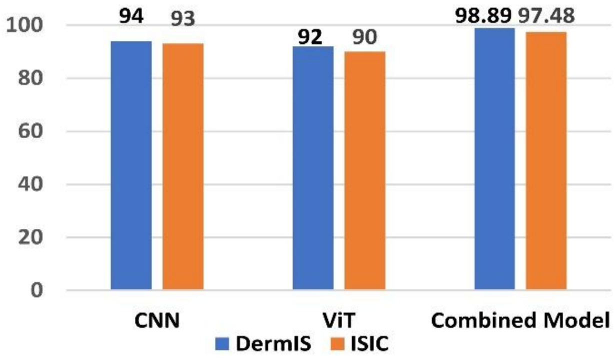

Fig. 7: Results comparison a. DermIS, b. ISIC Dataset

The combined model consistently outperforms individual CNN and ViT models on both datasets, though performance is slightly better on ISIC due to its more precise patterns and reduced complexity. The DermIS dataset challenges the models with more complex features. However, the ensemble approach remains the most effective across both datasets, highlighting the advantage of leveraging local and global feature extraction. A comparison of the results with ISIC and ISIC 2019 dataset is shown in Table 3.

Table III: Comparison of proposed model with ISIC 2019 Dataset (A: Accuracy, P: Precision, S: Sensitivity, Sp: Specificity, F1: F1-Score)

Results metrics	Results %	Methodology
A, P, S, Sp	94.92,80.36,79.8, 97	Transfer learning and pre-trained deep neural network GoogleNet [27]
A, S, Sp	91.89, 90.00, 94.12	InSiNet architecture (Deep CNN) [28]
A, P, S, Sp	96.7, 95.1, 96.3, 97.1	Hybrid CNN, and the VGG-19[29]
A, P, S, F1	**98.89, 100, 100, 100**	**Combined CNN and ViT[ours]**

The proposed model, which merges CNN and Vision Transformer (ViT), significantly outperforms other referenced methods on the ISIC 2019 dataset. It achieves an impressive accuracy of 98.89% and perfect scores in precision, sensitivity, and F1-measure, all at 100%. In contrast, methods using architectures like GoogleNet (Kassem et al., 2020), InSiNet (Reis et al., 2022), and a hybrid CNN-VGG19 (Alizadeh & Mahloojifar, 2021) approach only reached accuracies of 94.92%, 91.89%, 96.7%, and 97.49%, respectively, with lower precision and sensitivity. The fusion of CNN's feature extraction capabilities with ViT's advanced vision processing enhances generalization and robustness, leading to superior overall performance.

V. CONCLUSION AND FUTURE WORK

The research utilized Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) to improve skin cancer detection. Initially, custom architectures for both ViT and CNN were designed. The datasets were pre-processed with various transformations, and specialized data loaders were created for training and validation. The training process involved multiple epochs, using the Adam optimizer and cross-entropy loss to refine the ViT model. Metrics such as training and validation losses and accuracy were monitored throughout. Post each epoch, the model's performance was evaluated on the validation dataset, and the model's state was saved. Training and validation metrics were visualized using matplotlib. The study aimed to combine the strengths of CNNs and ViTs to enhance detection accuracy. Separate CNN and ViT models were created, trained, and evaluated for accuracy and speed. Ultimately, combining both models resulted in the highest accuracy on both datasets, highlighting the effectiveness of integrating CNNs and ViTs for skin cancer detection.

In skin cancer detection, future research focuses on advanced neural network architectures like novel versions of CNNs and ViTs to improve accuracy and efficiency. Integrating multimodal data, including patient demographics and genetic information, alongside imaging data could boost predictive power. Transfer learning and pretraining on extensive medical imaging datasets can speed up convergence and enhance generalization, especially with limited labeled data. Enhancing attention mechanisms in ViTs may improve feature extraction and contextual understanding in skin lesion images. Developing interpretable AI techniques can build trust among healthcare professionals, aiding their integration into clinical environments. Comprehensive evaluation through extensive clinical trials and real-world validation is crucial to determine AI systems' effectiveness, safety, and impact on skin cancer detection. Utilizing these systems in telemedicine and mobile health applications could expand access to early screening, particularly in underserved areas. The lack of large-scale clinical datasets is still a challenge.

VI. REFERENCES

Ain, Q. U., Khan, M. A., Yaqoob, M. M., Khattak, U. F., Sajid, Z., Khan, M. I., & Al-Rasheed, A. (2023). Privacy-aware collaborative learning for skin cancer prediction. Diagnostics, 13(13), 2264.

Aladhadh, S., Alsanea, M., Aloraini, M., Khan, T., Habib, S., & Islam, M. (2022). An effective skin cancer classification mechanism via medical vision transformer. Sensors, 22(11), 4008.

Albahar, M. A. (2019). Skin lesion classification using convolutional neural network with novel regularizer. IEEE Access, 7, 38306-38313.

Alizadeh, S. M., & Mahloojifar, A. (2021). Automatic skin cancer detection in dermoscopy images by combining convolutional neural networks and texture features. International Journal of Imaging Systems and Technology, 31(2), 695-707.

Argenziano, G., Soyer, H. P., De Giorgi, V., Piccolo, D., Carli, P., & Delfino, M. (2000). Interactive atlas of dermoscopy (Book and CD-ROM).

Aswin, R. B., Jaleel, J. A., & Salim, S. (2014, July). Hybrid genetic algorithm—Artificial neural network classifier for skin cancer detection. In 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT) (pp. 1304-1309). IEEE.

Boer, A., & Nischal, K. C. (2007). www. derm101. com: A growing online resource for learning dermatology and dermatopathology. Indian Journal of Dermatology, Venereology and Leprology, 73, 138.

DermIS. Available from: https://www.dermis.net/dermisroot/en/home/index.htm

Dermnet. Available from: http://www.dermnet.com/dermatology-pictures-skin-disease-pictures/

Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., ... & Mahnashi, M. H. (2021). Skin cancer detection: a review using deep learning techniques. International journal of environmental research and public health, 18(10), 5479.

Dosovitskiy, A. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929.

Doukas, C., Stagkopoulos, P., Kiranoudis, C. T., & Maglogiannis, I. (2012, August). Automated skin lesion assessment using mobile technologies and cloud platforms. In 2012 Annual international conference of the IEEE Engineering in Medicine and Biology Society (pp. 2444-2447). IEEE.

Giotis, I., Molders, N., Land, S., Biehl, M., Jonkman, M. F., & Petkov, N. (2015). MED-NODE: A computer-assisted melanoma diagnosis system using non-dermoscopic images. Expert systems with applications, 42(19), 6578-6585.

Hosny, K. M., Kassem, M. A., & Foaud, M. M. (2019). Classification of skin lesions using transfer learning and augmentation with Alex-net. PloS one, 14(5), e0217293.

ISIC Archive. Available from: https://isic-archive.com/

Jemal, A., Devesa, S. S., Hartge, P., & Tucker, M. A. (2001). Recent trends in cutaneous melanoma incidence among whites in the United States. Journal of the National Cancer Institute, 93(9), 678-683.

Kaggle Skin Cancer ISIC. Available from: https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic

Kanimozhi, T., & Murthi, A. (2016). Computer aided melanoma skin cancer detection using artificial neural network classifier. Singaporean Journal of Scientific Research (SJSR), Journal of Selected Areas in Microelectronics (JSAM), 8(2), 35-42.

Kassem, M. A., Hosny, K. M., & Fouad, M. M. (2020). Skin lesions classification into eight classes for ISIC 2019 using deep convolutional neural network and transfer learning. IEEE access, 8, 114822-114832.

Khan, M. A., Sharif, M., Akram, T., Bukhari, S. A. C., & Nayak, R. S. (2020). Developed Newton-Raphson based deep features selection framework for skin lesion recognition. Pattern Recognition Letters, 129, 293-303.

Khan, M. Q., Hussain, A., Rehman, S. U., Khan, U., Maqsood, M., Mehmood, K., & Khan, M. A. (2019). Classification of melanoma and nevus in digital images for diagnosis of skin cancer. IEEE Access, 7, 90132-90144.

Masood, A., Al-Jumaily, A. A., & Adnan, T. (2014, September). Development of automated diagnostic system for skin cancer: Performance analysis of neural network learning algorithms for classification. In International Conference on Artificial Neural Networks (pp. 837-844). Cham: Springer International Publishing.

Murugan, A., Nair, S. A. H., & Kumar, K. S. (2019). Detection of skin cancer using SVM, random forest and kNN classifiers. Journal of medical systems, 43(8), 269.

Nachbar, F., Stolz, W., Merkle, T., Cognetta, A. B., Vogt, T., Landthaler, M., ... & Plewig, G. (1994). The ABCD rule of dermatoscopy: high prospective value in the diagnosis of doubtful melanocytic skin lesions. Journal of the American Academy of Dermatology, 30(4), 551-559.

Pacheco, A. G., & Krohling, R. A. (2019). Recent advances in deep learning applied to skin cancer detection. arXiv preprint arXiv:1912.03280.

Reis, H. C., Turk, V., Khoshelham, K., & Kaya, S. (2022). InSiNet: a deep convolutional approach to skin cancer detection and segmentation. Medical & Biological Engineering & Computing, 60(3), 643-662.

Sajid, P. M., & Rajesh, D. A. (2018). Performance evaluation of classifiers for automatic early detection of skin cancer. J. Adv. Res. Dyn. Control. Syst, 10, 454-461.

Xie, F., Fan, H., Li, Y., Jiang, Z., Meng, R., & Bovik, A. (2016). Melanoma classification on dermoscopy images using a neural network ensemble model. IEEE transactions on medical imaging, 36(3), 849-858.

Zhang, N., Cai, Y. X., Wang, Y. Y., Tian, Y. T., Wang, X. L., & Badami, B. (2020). Skin cancer diagnosis based on optimized convolutional neural network. Artificial intelligence in medicine, 102, 101756.