Journal for Educators, Teachers and Trainers
The PROFESIOLab electronic, peer-reviewed, open-access Magazine

ISSN 1989-9572

DOI:10.47750/jett.2023.14.05.058

EXPLORING DEEP LEARNING TECHNIQUES FOR ADVANCED SKIN CANCER DETECTION AND MULTI-CLASS CLASSIFICATION IN DERMATOLOGICAL IMAGING

Chigurlapalli Swathi[1],
Dr P Hasitha Reddy[1],
Sowbhagya Juttu[1]

Journal for Educators, Teachers and Trainers, Vol.14(5)

https://jett.labosfor.com/

Date of reception: 18 July 2023

Date of revision: 09 Aug 2023

Date of acceptance: 21 Sep 2023

A Chigurlapalli Swathi, Dr P Hasitha Reddy, Sowbhagya Juttu (2023). EXPLORING DEEP LEARNING TECHNIQUES FOR ADVANCED SKIN CANCER DETECTION AND MULTI-CLASS CLASSIFICATION IN DERMATOLOGICAL IMAGING. Journal for Educators, Teachers and Trainers, Vol. 14(5). 647-655.

Journal for Educators, Teachers and Trainers
The LabOSfor electronic, peer-reviewed, open-access Magazine

Journal for Educators, Teachers and Trainers
The PROFESIOLab electronic, peer-reviewed, open-access Magazine

Journal for Educators, Teachers and Trainers, Vol. 14(5)

ISSN 1989 –9572

https://jett.labosfor.com/

EXPLORING DEEP LEARNING TECHNIQUES FOR ADVANCED SKIN CANCER DETECTION AND MULTI-CLASS CLASSIFICATION IN DERMATOLOGICAL IMAGING

Chigurlapalli Swathi[1],Dr P Hasitha Reddy[1],Sowbhagya Juttu[1]
[1]Department of Computer Science Engineering,
[1]Sree Dattha Group of Institutions, Sheriguda, Hyderabad, Telangana

ABSTRACT

Given the prevalence and occasionally lethal nature of skin cancer, early detection is crucial for successful treatment. In this study, we propose a deep learning model for the multi-class classification and identification of skin cancer lesions. Skin cancer, a serious worldwide health issue, is detected using conventional techniques that mostly rely on dermatologists' expertise. These techniques can be challenging to use, subjective, and lead to delays in diagnosis. These drawbacks might result in missed chances for early intervention. To address these issues, we propose a deep learning-based system to automatically detect and categorize skin cancer lesions into many categories, including melanoma, basal cell carcinoma, and squamous cell carcinoma. Apart from surmounting the limitations of conventional methods, our proposed system offers scalability, consistency, and potential for increased accessibility, all of which have the potential to improve the accuracy and timelyness of skin cancer detection. We evaluate the model on a large dataset, demonstrating its utility in aiding dermatologists and other health care providers in the early diagnosis and treatment of skin cancer, which would eventually improve patient outcomes and streamline healthcare delivery.

Keywords: Skin Cancer, Deep Learning, Classification, Diagnosis, Healthcare

1. INTRODUCTION

Skin cancer is a type of cancer that begins in the skin cells. It occurs when skin cells undergo abnormal changes, usually due to exposure to ultraviolet (UV) radiation from the sun or tanning beds. The three main types of skin cancer are basal cell carcinoma, squamous cell carcinoma, and melanoma. Basal cell carcinoma is the most common type, typically appearing as a shiny bump or a pink growth on the skin. Squamous cell carcinoma often presents as a firm, red nodule or a flat sore, and it can sometimes develop into deeper layers of the skin. Melanoma is less common but more dangerous, arising from the pigment-producing cells called melanocytes and often appearing as a mole with irregular borders and multiple colors.

Early detection of skin cancer is crucial for successful treatment. Regular self-examination of the skin and routine visits to a dermatologist can help detect any suspicious changes early on. Treatment options for skin cancer vary depending on the type, size, location, and stage of the cancer. They may include surgical removal, chemotherapy, radiation therapy, immunotherapy, or targeted therapy. In many cases, surgery is sufficient to remove the cancerous cells completely, especially if detected early.Prevention is key in reducing the risk of developing skin cancer. Limiting exposure to UV radiation by seeking shade, wearing protective clothing, and using sunscreen with a high SPF can help prevent skin damage and reduce the likelihood of developing skin cancer. Avoiding tanning beds and sunlamps is also important, as they emit harmful UV radiation that can increase the risk of skin cancer. Additionally, individuals with fair skin, light-colored eyes, a history of sunburns, or a family history of skin cancer may be at a higher risk and should take extra precautions to protect their skin.

Despite efforts to prevent skin cancer, it remains a significant health concern worldwide. The incidence of skin cancer continues to rise, particularly in regions with high levels of UV radiation exposure. Education about the risks of UV radiation and the importance of sun safety practices is essential in raising awareness and promoting early detection and treatment. By adopting sun-safe behaviors and regularly monitoring their skin for any changes, individuals can take proactive steps to reduce their risk of developing skin cancer and maintain overall skin health

2. LITERATURE SERVEY

Mazhar, et. al [1] This article described the fundamentals of ML-based implementations, as well as future limits and concerns for the production of skin cancer detection and classification systems. It also explored five fields of dermatology using deep learning applications: (1) the classification of diseases by clinical photos, (2) dermato pathology visual classification of cancer, and (3) the measurement of skin diseases by smartphone applications and personal tracking systems. This analysis aimed to provide dermatologistswith a guide that helped demystify the basics of ML and its different applications to identify their possible challenges correctly. The paper surveyed studies on skin cancer detection using deep learning to assess the features and advantages of other techniques. Moreover, the paper also defined the basic requirements for creating a skin cancer detection application, which revolved around two main issues: the full segmentation image and the tracking of the lesion on the skin using deep learning. Most of the techniques found in this survey addressed these two problems. Some of the methods also categorized the type of cancer too.

Bhatt, et. al [2] Skin cancer was among the most common and lethal cancer types, with the number of cases increasing dramatically worldwide. If not diagnosed in the nascent stages, it could lead to metastases, resulting in high mortality rates. Skin cancer could be cured if detected early. Consequently, timely and accurate diagnosis of such cancers was currently a key research objective. Various machine learning technologies had been employed in computer-aided diagnosis of skin cancer detection and malignancy classification. Machine learning was a subfield of artificial intelligence (AI) involving models and algorithms which could learn from data and generate predictions on previously unseen data. The traditional biopsy method was applied to diagnose skin cancer, which was a tedious and expensive procedure. Alternatively, machine learning algorithms for cancer diagnosis could aid in its early detection, lowering the workload of specialists while simultaneously enhancing skin lesion diagnostics. This article presented a critical review of select state-of-the-art machine learning techniques used to detect skin cancer. Several studies had been collected, and an analysis of the performance of k-nearest neighbors, support vector machine, and convolutional neural networks algorithms on benchmark datasets was conducted. The shortcomings and disadvantages of each algorithm were briefly discussed. Challenges in detecting skin cancer were highlighted, and the scope for future research was proposed.

Inthiyaz, et.al [3] This work provided an automated image-based method for diagnosing and categorizing skin problems that used machine learning classification. Computational approaches were used to analyze, process, and relegate picture data to consider the many different characteristics of the photos that were being processed. Skin photographs were first filtered to remove undesirable noise from the image and then processed to enhance the picture's overall quality. It was possible to extract features from an image using advanced techniques such as Convolutional Neural Network (CNN), classify the picture using the softmax classifier's algorithm, and provide a diagnostic report as an output. With more accuracy and faster delivery of results than the previous technique, this application became a more efficient and reliable system for dermatological illness diagnosis than the conventional method. Furthermore, this could be a reliable real-time teaching tool for medical students enrolled in the dermatology stream at a university studying dermatology.

Zafar, et. al [4] This research provided an extensive literature review of the methodologies, techniques, and approaches applied for the examination of skin lesions to date. This survey included preprocessing, segmentation, feature extraction, selection, and classification approaches for skin cancer recognition. The results of these approaches were very impressive, but still, some challenges occurred in the analysis of skin lesions because of complex and rare features. Hence, the main objective was to examine the existing techniques utilized in the discovery of skin cancer by finding the obstacle that helped researchers contribute to future research.

Tumbhurne, et. al [5] The deep learning model used state-of-the-art neural networks to extract features from images, whereas the machine learning model processed image features obtained after performing techniques such as Contourlet Transform and Local Binary Pattern Histogram. Meaningful feature extraction was crucial for any image classification problem. As a result, by combining the manual and automated features, their designed model achieved a higher accuracy of 93% with an individual recall score of 99.7% and 86% for the benign and malignant forms of cancer, respectively. They benchmarked the model on a publicly available Kaggle dataset containing processed images from the ISIC Archive dataset. The proposed ensemble outperformed both expert dermatologists as well as other state-of-the-art deep learning and machine learning methods. Thus, this novel method could be of high assistance to dermatologists to help prevent any misdiagnosis.

Tabrizchi, et. al [6] This study presented a new model for the early detection of skin cancer based on processing dermoscopic images. The model worked based on a well-known CNN-based architecture called the VGG-16 network. The proposed framework employed an enhanced architecture of VGG-16 to develop a model, which contributed to the improvement of accuracy in skin cancer detection. To evaluate the proposed technique, they conducted a comparative study between their method and a number of previously introduced techniques on the International Skin Image Collaboration dataset. According to the results, the proposed model outperformed the compared alternative techniques in terms of accuracy.

Tahir, et. al [7] the application of deep learning (DL) algorithms for the detection of skin cancer had grown in popularity. Based on a DL model, this work intended to build a multi-classification technique for diagnosing skin cancers such as melanoma (MEL), basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanocytic nevi (MN). In this paper, they proposed a novel model, a deep learning-based skin cancer classification network (DSCC_Net) that was based on a convolutional neural network (CNN), and evaluated it on three publicly available benchmark datasets (i.e., ISIC 2020, HAM10000, and DermIS). For the skin cancer diagnosis, the classification performance of the proposed DSCC_Net model was compared with six baseline deep networks, including ResNet-152, Vgg-16, Vgg-19, Inception-V3, EfficientNet-B0, and MobileNet. Additionally, they used SMOTE Tomek to handle the minority classes issue that existed in this dataset. The proposed DSCC_Net obtained a 99.43% AUC, along with a 94.17% accuracy, a recall of 93.76%, a precision of 94.28%, and an F1-score of 93.93% in categorizing the four distinct types of skin cancer diseases. The rates of accuracy for ResNet-152, Vgg-19, MobileNet, Vgg-16, EfficientNet-B0, and Inception-V3 were 89.32%, 91.68%, 92.51%, 91.12%, 89.46%, and 91.82%, respectively.

Mangione, et. al [8] Skin cancer was the most commonly diagnosed cancer in the US. There were different types of skin cancer varying in disease incidence and severity. Basal and squamous cell carcinomas were the most common types of skin cancer but infrequently led to death or substantial morbidity. Melanomas represented about 1% of skin cancer and caused the most skin cancer deaths. Melanoma was about 30 times more common in White persons than in Black persons. However, persons with darker skin color were often diagnosed at later stages, when skin cancer was more difficult to treat.

Priyadharshini, et. al [9]This paper proposed a novel hybrid Extreme Learning Machine (ELM) and Teaching–Learning-Based Optimization (TLBO) algorithm as a versatile technique for detecting melanoma. ELM was a single-hidden layer feed-forward neural network that could be trained quickly and accurately, while TLBO was an optimization algorithm used to fine-tune the network's parameters for improved performance. Together, these techniques could classify skin lesions as benign or malignant images, potentially improving melanoma detection accuracy.

3. PROPOSED METHODOLOGY

3.1 Overview

The GAN-generated images are also passed through the trained DLCNN model for prediction. This helps in evaluating the generalization capability of the model to synthetic data and assessing its robustness in real-world scenarios.

Based on the predictions made by the DLCNN model, each skin lesion image is classified into different types of skin cancer, providing valuable insights for early diagnosis and treatment planning.

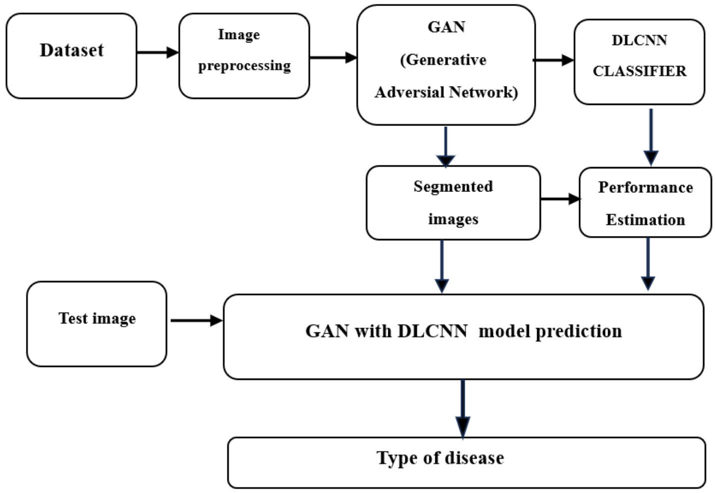

Figure 1: Block Diagram of Proposed Model.

3.2 DLCNN CLASSIFIER

Convolution Layer: in a deep learning convolutional neural network (cnn) classifier, convolutional layers play a fundamental role in feature extraction. these layers are inspired by the visual cortex of the human brain, where neurons respond to specific stimuli in limited regions of the visual field, enabling hierarchical feature representation. in a cnn, each convolutional layer consists of multiple filters or kernels, which are small learnable matrices applied across the input image to extract various features.

Maxpooling Layer: maxpooling serves several purposes within a cnn classifier. firstly, it helps in reducing the computational complexity of the network by downsampling the feature maps, which leads to faster training and inference times. secondly, it introduces a form of translation invariance by selecting the most prominent features within each local region, making the network more robust to small spatial translations of objects in the input images. lastly, maxpooling aids in feature abstraction and generalization by summarizing local information while preserving important patterns and structures.

Relu Activation: in deep learning convolutional neural network (cnn) classifiers, the rectified linear unit (relu) activation function plays a crucial role in introducing non-linearity into the network's computations. relu is a simple yet effective activation function widely used in various neural network architectures, including cnns. its popularity stems from its computational efficiency and its ability to address the vanishing gradient problem.

Dense Layer: the dense layer, also known as a fully connected layer, is typically placed towards the end of the cnn architecture. its primary function is to perform classification based on the features extracted by earlier layers. each neuron in the dense layer is connected to every neuron in the preceding layer, allowing it to learn complex patterns and relationships in the data. these connections are learned through the training process, where the network adjusts the weights associated with each connection to minimize the classification error**.**

Flatten Layer: The Flatten layer, on the other hand, serves as a bridge between the convolutional layers and the Dense layers. In CNNs, convolutional layers process input data in the form of multi-dimensional arrays (tensors), preserving spatial information such as height, width, and channels. However, Dense layers require one-dimensional input vectors. The Flatten layer resolves this disparity by reshaping the output of the last convolutional layer into a one-dimensional vector, effectively "flattening" it. This transformation allows the subsequent Dense layers to operate on the extracted features in a format suitable for classification**.**

Fully Connected Layer: The fully connected layer connects every neuron in one layer to every neuron in the next layer, forming a dense network of connections. Each neuron in the fully connected layer receives input from all the neurons in the preceding layer, allowing it to consider the entirety of the feature information captured in the previous layers. This comprehensive connection scheme enables the network to learn complex relationships between features extracted from the input data.

Softmax Classifier: The softmax classifier works by first computing the raw scores for each class based on the features extracted by the preceding layers. These scores are then transformed into probabilities through the softmax function, which ensures that they sum up to 1. Each class probability represents the model's confidence in predicting that particular class given the input data.

Adam Optimization (Adaptive Moment Estimation):ADAM maintains two moving averages: the first moment (mean) of the gradients and the second moment (uncentered variance) of the gradients. These moving averages are utilized to adaptively adjust the learning rate for each parameter during training. The algorithm computes an individual learning rate for each parameter based on the magnitude of its gradient and the magnitude of the past gradients. This adaptive learning rate scheme allows ADAM to converge faster and more reliably compared to fixed learning rate methods**.**

Binary Cross Entropy Loss Reduction: The binary cross-entropy loss is then calculated using these predicted probabilities and the actual binary labels. Through backpropagation, gradients of the loss with respect to the model parameters are computed, allowing the optimizer to update the parameters in a direction that minimizes the loss.

4. RESULTS AND DISCUSSION

This figure 2 shows the graphical user interface (GUI) of the skin cancer detection application. It includes various buttons, text fields, and other interactive elements for users to interact with the application. The interface provides a user-friendly way to access different functionalities such as loading models, preprocessing images, and viewing results.

Figure 2:User interface of Skin Cancer Detection.

Metric	Existing Alexnet Model	Propose GAN Segmented Model
Accuracy	92.090	96.426
Precision	88.255	98.233
Recall	92.781	97.821
F1 Score	89.403	97.931
Sensitivity	1.000	1.000
Specificity	1.000	1.000

Table 1: Performance comparison.

Table 1: compares the performance metrics of the existing AlexNet model and the proposed GAN segmented model for skin cancer detection. Metrics such as accuracy, precision, recall, F1 score, sensitivity, and specificity are provided for both models. It highlights the differences in performance between the two models across various evaluation criteria.

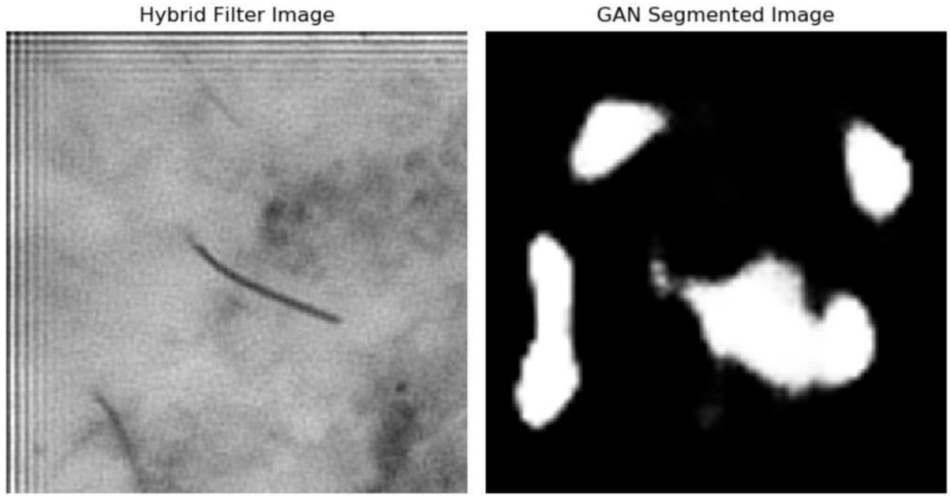

Figure 3:Segmentation Outcome from GAN model.

Figure 3 presents the segmentation outcome obtained from the GAN (Generative Adversarial Network) model. The GAN model segments the input image into different regions or classes corresponding to different skin lesion types. The segmented image provides insights into how the GAN model separates different regions of interest in the image. Figure 4 illustrates the comparison of performance metrics (e.g., accuracy, loss) between the existing AlexNet model and the proposed GAN segmented model across multiple epochs. Each epoch represents a complete pass through the entire training dataset during model training. The graph helps visualize the convergence and relative performance of both models over time.

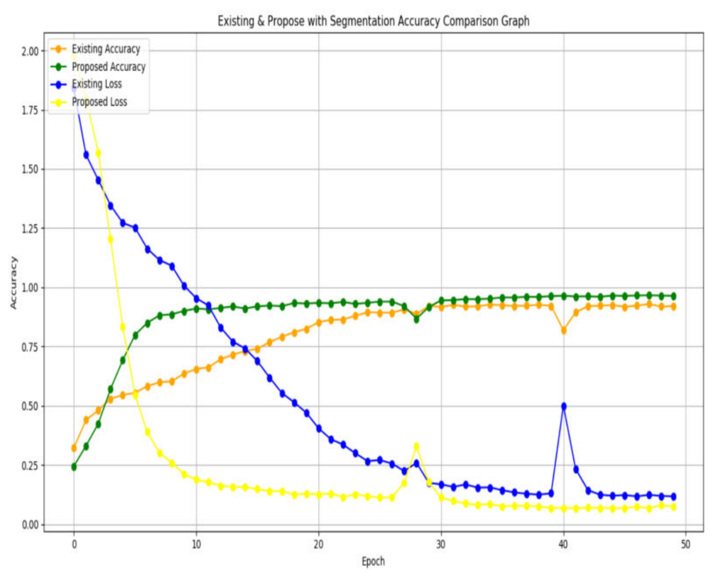

Figure 4:comparison graph of Existing and proposed model per epoch.

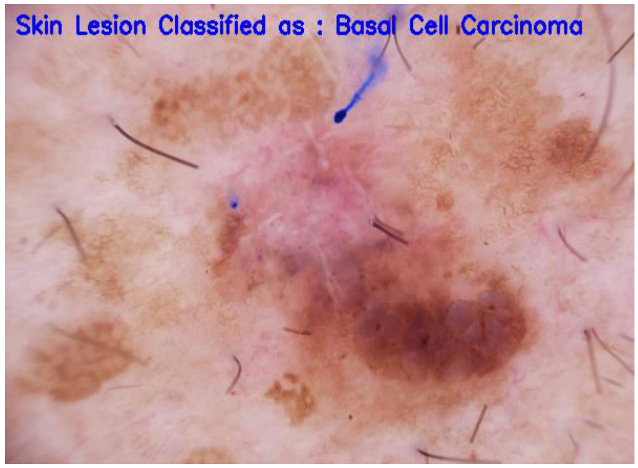

Figure 5: Proposed model disease prediction on test image.

Figure 5 shows that demonstrates the disease prediction outcome of the proposed model on a test image. The image contains a skin lesion, and the model predicts the type or severity of the disease present in the lesion. The predicted disease class is overlaid or displayed alongside the original image to provide visual feedback to the user.

5. CONCLUSION

The development of deep learning models for skin cancer detection and multi-class classification represents a significant advancement in the field of medical imaging and dermatology. These models leverage complex neural networks to analyze vast amounts of dermatological images, providing accurate and efficient diagnosis for various types of skin lesions. Through the utilization of convolutional neural networks (CNNs) and other deep learning architectures, these models have demonstrated remarkable capabilities in distinguishing between benign and malignant lesions, as well as classifying different types of skin cancers based on their characteristics.One of the key strengths of these deep learning models is their ability to learn intricate patterns and features from dermatological images, surpassing traditional methods in accuracy and reliability. By training on large datasets containing diverse examples of skin lesions, these models can generalize well to new cases, enabling them to effectively handle real-world scenarios. Additionally, the continuous refinement of these models through techniques such as transfer learning and data augmentation further enhances their performance and robustness, ensuring consistent and reliable results across different settings and populations.The deployment of deep learning models for skin cancer detection and classification has the potential to revolutionize clinical practice by providing dermatologists and healthcare professionals with valuable decision support tools. These models can aid in the early detection of skin cancer, leading to timely interventions and improved patient outcomes. Furthermore, their ability to accurately classify lesions into multiple categories facilitates personalized treatment plans, optimizing patient care and management strategies.Despite their considerable promise, the integration of deep learning models into clinical practice also presents several challenges and considerations. Ensuring the ethical and responsible deployment of these models requires careful validation and rigorous evaluation to mitigate potential biases and errors. Moreover, addressing concerns regarding data privacy and security is essential to maintain patient trust and confidentiality in the healthcare setting. Additionally, ongoing research and collaboration are needed to refine and optimize these models, addressing limitations and improving their performance in real-world settings.The development and implementation of deep learning models for skin cancer detection and multi-class classification represent a significant step forward in the field of dermatology and medical imaging. These models offer unparalleled accuracy and efficiency in diagnosing and classifying skin lesions, with the potential to revolutionize clinical practice and improve patient outcomes. However, their integration into healthcare systems must be accompanied by careful validation, ethical considerations, and ongoing refinement to ensure their safe and effective use in improving patient care.

REFERENCES

[1] Mazhar, Tehseen, Inayatul Haq, Allah Ditta, Syed Agha HassnainMohsan, Faisal Rehman, Imran Zafar, Jualang Azlan Gansau, and Lucky Poh Wah Goh. "The role of machine learning and deep learning approaches for the detection of skin cancer." In Healthcare, vol. 11, no. 3, p. 415. MDPI, 2023.

[2] Bhatt, Harsh, Vrunda Shah, Krish Shah, Ruju Shah, and Manan Shah. "State-of-the-art machine learning techniques for melanoma skin cancer detection and classification: a comprehensive review." Intelligent Medicine 3, no. 03 (2023): 180-190.

[3] Inthiyaz, Syed, Baraa Riyadh Altahan, SkHasane Ahammad, V. Rajesh, Ruth Ramya Kalangi, Lassaad K. Smirani, Md Amzad Hossain, and Ahmed Nabih Zaki Rashed. "Skin disease detection using deep learning." Advances in Engineering Software 175 (2023): 103361.
[4] Zafar, Mehwish, Muhammad Imran Sharif, Muhammad Irfan Sharif, Seifedine Kadry, Syed Ahmad Chan Bukhari, and Hafiz Tayyab Rauf. "Skin lesion analysis and cancer detection based on machine/deep learning techniques: A comprehensive survey." Life 13, no. 1 (2023): 146.
[5] Tembhurne, Jitendra V., Nachiketa Hebbar, Hemprasad Y. Patil, and Tausif Diwan. "Skin cancer detection using ensemble of machine learning and deep learning techniques." Multimedia Tools and Applications (2023): 1-24.
[6] Tabrizchi, Hamed, Sepideh Parvizpour, and Jafar Razmara. "An improved VGG model for skin cancer detection." Neural Processing Letters 55, no. 4 (2023): 3715-3732.
[7] Tahir, Maryam, Ahmad Naeem, Hassaan Malik, Jawad Tanveer, Rizwan Ali Naqvi, and Seung-Won Lee. "DSCC_Net: Multi-Classification Deep Learning Models for Diagnosing of Skin Cancer Using Dermoscopic Images." Cancers 15, no. 7 (2023): 2179.
[8] Mangione, Carol M., Michael J. Barry, Wanda K. Nicholson, David Chelmow, Tumaini Rucker Coker, Esa M. Davis, Katrina E. Donahue et al. "Screening for skin cancer: US preventive services task force recommendation statement." Jama 329, no. 15 (2023): 1290-1295.
[9] Priyadharshini, N., N. Selvanathan, B. Hemalatha, and C. Sureshkumar. "A novel hybrid Extreme Learning Machine and Teaching–Learning-Based Optimization algorithm for skin cancer detection." Healthcare Analytics 3 (2023): 100161.