IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Towards Enhanced Melanoma Skin Cancer Detection Using Image Processing and Transfer Learning

[1] Hussaini Aliyu Idris, [2]Muhammad Adamu, [3]Umar Abubakar Tsakuwa,[4]Khalid Haruna

[1]Dept. of Computer Science, Jigawa State Polytechnic Dutse, PMB 7001 Dutse, Nigeria.
[2] Dept. of Electrical and Electronics Engineering Technology, Jigawa State Polytechnic Dutse, Nigeria.
[3,4]Department of Computer Science, Bayero University Kano, Nigeria.

Abstract : Melanoma, a life-threatening form of skin cancer caused by DNA damage from ultraviolet radiation, poses a significant health risk. Early detection plays a critical role in successful treatment outcomes. In this paper, we present a novel approach for the detection of melanoma skin cancer using image processing techniques and transfer learning. Our proposed method aims to improve accuracy compared to existing state-of-the-art techniques. We conducted extensive experiments using the publicly available MED-NODE skin cancer dataset, which comprises high-resolution skin lesion images. Our approach leverages image processing algorithms to extract relevant features and employs transfer learning with pre-trained models to enhance classification performance. By fine-tuning a pre-trained model specifically VGG19, we capitalize on the learned representations from a large dataset like ImageNet. The results of our experiments demonstrate the superiority of the proposed approach, exhibiting an impressive improvement of approximately 10% in accuracy compared to existing methods. The validation of our approach using the MED-NODE skin cancer dataset further strengthens its effectiveness in melanoma detection

***IndexTerms* - artificial intelligence, convolutional neural network (CNN), image processing, malenoma, transfer learning, ,**

INTRODUCTION

The integumentary system, comprising the skin, plays a crucial role to safeguard internal human organs from external harm. However, the skin is susceptible to various diseases which at a time can be life-threatening. One such perilous condition is skin cancer that usually manifests in three primary forms: basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma and Merkel cell carcinoma (MCC)[1]. Among, the melanoma poses the greatest risk as it exhibits rapid growth and has metastasize potentiality [2]. Alarming data from the World Health Organization (WHO) reveals that skin cancer accounts for one-third of all malignancies. Moreover, there has been a significant 55-percent increase in annual skin cancer cases from 2009 to 2019 [3]. In 2022, about 99,780 new cases of melanoma are projected to be diagnosed; with 7,650 individuals expected to succumb to melanoma skin cancer that year[4].

The risk of developing melanoma varies among different ethnic groups with White individuals having lifetime risk of approximately 2.6% , 0.1% for Black individuals, and 0.6% for Hispanics[1]. Timely detection of early-stage melanoma is important for successful treatment as it improves the chances of survival, with rates exceeding 90 percent. Given the complexities associated with skin lesions, dermatologists rely on various visual assessments, such as evaluating the symmetry, size, shape, color, and border of a lesion, to diagnose malignant melanoma. The presence of an "ugly duckling" lesion serves as an additional warning sign. Several scoring techniques are commonly employed to identify malignant melanoma, including the 7-point checklist, Menzies method, 3-point checklist, and ABCDE rules. Among these, the ABCDE rule is widely utilized and encompasses asymmetry (one half of the mole differing from the other), border irregularity, non-uniform color, a diameter greater than 6mm, and evolving size, shape, or color [5].

To assess the size, color, and texture of a mole, specialized physicians scrutinize lesion areas and calculate the total dermatoscopic score (TDS) using the ABCDE criteria and corresponding weight factors[6]. The diagnosis is then determined based on the TDS value; if the TDS surpasses a predetermined threshold, the lesion is identified as malignant and a value below the threshold indicates a benign condition. Nonetheless, this detection process is time-consuming and heavily reliant on the expertise of specialist doctors, making it prone to inconsistencies due to subjective interpretation. To address the limitations involved, computerized artificial intelligence (AI)-based systems is a potential solution for accurate and efficient detection of melanoma from normal skin and the interpretation of the predictions made [7]. In recent years, convolutional neural networks (CNNs) have increasingly been employed in medical imaging applications. In addition to the advancements provided by Convolutional Neural Networks (CNNs) in image classification tasks, transfer learning has emerged as a valuable technique in leveraging pre-trained models to tackle new classification problems[8]. Transfer learning allows the knowledge gained from training on large-scale datasets to be transferred and applied to related tasks with limited labeled data available as in this case of study.

One prominent pre-trained model used in transfer learning is the VGG19 architecture. VGG19 has demonstrated remarkable success in image classification tasks due to its deep structure and homogeneous architecture. It consists of 19 layers, including convolutional layers with small receptive fields, followed by max-pooling layers, and fully connected layers [9],[10].

By utilizing VGG19 as a pre-trained model, the network can leverage the learned features from a large dataset, such as ImageNet, which consists of millions of labeled images. This pre-training provides a strong foundation for the network to extract high-level features from images, even when working with a smaller, task-specific dataset. Fine-tuning the pre-trained VGG19 model on the target dataset allows for efficient learning and improved classification performance, even in scenarios where limited labeled data is available.

The VGG19 architecture has proven to be effective in capturing intricate image features, making it especially suitable for image classification problems. By utilizing the transfer learning approach with VGG19, the network can benefit from the rich feature representations learned from ImageNet, ultimately enhancing the accuracy and generalization capabilities of the model in the target classification task.

In this study, we propose an intelligent system that leverages image processing, and transfer learning techniques to detect melanoma and nevus moles at an early stage. By addressing the intricacies associated with this issue, our innovative approach aims to mitigate the shortcomings of current detection procedures**.**

The rest of this paper is organized as follows: review of related literatures is presented in section 2; section 3 contains the description of the proposed approach. The results analysis and discussion are presented in section 4 and then follow by a section which comprises of conclusion and direction of future work.

RELATED WORK REVIEW

In the study conducted by the authors in [11], they worked with the MED-NODE dataset to segment regions of interest in healthy and lesioned areas. To handle noise and illumination effectively, they performed a series of pre-processing steps. Gaussian smoothing with a parameter of $\sigma = 5$ and Kuwahara smoothing filters were applied to remove noise while preserving edges. After noise removal, each image was divided into 50 sub-images with a pixel size of 15 × 15. The authors acknowledged that although their model was effective, the limited size of the dataset was a major limitation.

In another study by the authors in [12], a deep neural model was proposed. They aimed to reduce the effects of illumination and noise in the pre-processing step. The enhanced images were then fed into a pre-trained CNN model. As the dataset had a limited number of images, the authors used cropping and rotation techniques to expand the training data. They generated a segmentation mask by applying the k-means classifier ($k = 2$) to the pre-processed image and enhanced the mask using morphological operations. A Gaussian filter was applied to the standard skin parts based on the information from the segmentation mask. Their CNN model consisted of 20 feature maps in the first convolution layer and 50 feature maps in the second convolution layer. Pooling layers and a two-layer fully connected stage were utilized after each convolution layer. The authors highlighted that the illumination correction improved their system's discrimination capability and increased accuracy.

In [3], the authors developed a combined model that employed multi-level segmentation, CNN, support vector machine (SVM), and back-propagation neural network techniques. They utilized the Otsu, modified Otsu, and watershed segmentation methods for segmentation and employed CNN and SVM for training and classification, respectively.

In the study mentioned by the authors in [5], MED-NODE dataset is utilized. In the pre-processing step, Otsu's segmentation method was applied to a grayscale image to segment the lesion part from the image. A total of 1900 features were extracted from each segmented lesion image. Out of these features, 25 were excluded as they were deemed too high, too low, or constant across the dataset. The feature set was tested with different types of training and cost functions in a multi-layer neural network (MLP). The relief method was used to rank the features, and the best-ranked features among the 1875 remaining features were selected. The classifiers used were MLP with PCA features, linear SVM, medium KNN, and linear discriminant. The MLP with PCA features, which utilized only 25 features, achieved an accuracy of 87.18%.

The work in [13] focuses on the effect of contrast enhancement and image texture analysis in an image classification model. They emphasized that contrast enhancement improves the discrimination between intensity values in an image, making them easily identifiable by both humans and computer vision systems. The authors recognized that image texture analysis plays a crucial role in pattern recognition due to its powerful discrimination ability.

THE PROPOSED METHOD

In this section, the four-phased methodology adopted in this research is discussed along with the dataset description, the proposed method employed for better accuracy. The detailed phases of the methodology is pictorially depicted in Figure 3.

3.1 Data Acquisition and Description

The proposed system was evaluated using the MED-NODE melanoma dataset, which is a publicly available dataset of high-resolution skin lesion images [11]. The MED-NODE dataset is a subset of a larger digital image archive containing 50,000 images collected by the Department of Dermatology at the University Medical Center Groningen (UMCG). All the images in this dataset were carefully examined and assessed by dermatologists to ensure their quality and accuracy. The images were captured in JPEG format using Nikkor lenses on Nikon D3 and D1x cameras, with a distance of approximately 33 cm from the skin lesion areas. Examples of images from the MED-NODE dataset can be seen in Figure 1 and Figure 2. To ensure the reliability of the dataset, the following criteria were considered [11]: (i) The MED-NODE dataset consists of 170 randomly chosen images, making it impossible to identify specific patient instances. (ii) The dataset includes images of superficial spreading melanoma and nevi, providing a diverse range of skin conditions. (iii) Each image originates from a different patient, except for one image that demonstrates how the disease varies in different areas of the body. And finally, (iv) Each image is labeled with the corresponding group to which it belongs, allowing for classification and analysis.

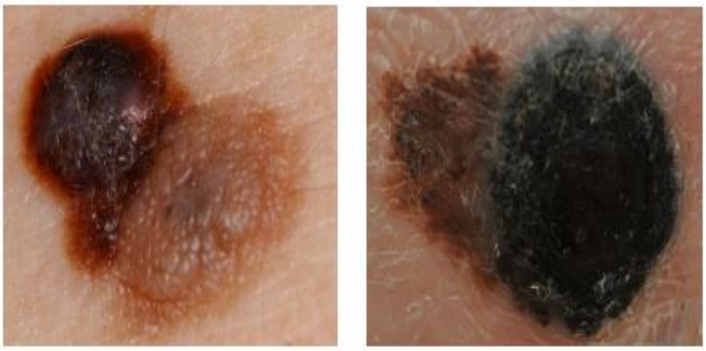

Figure 1: Melanoma Skin Cancer Images

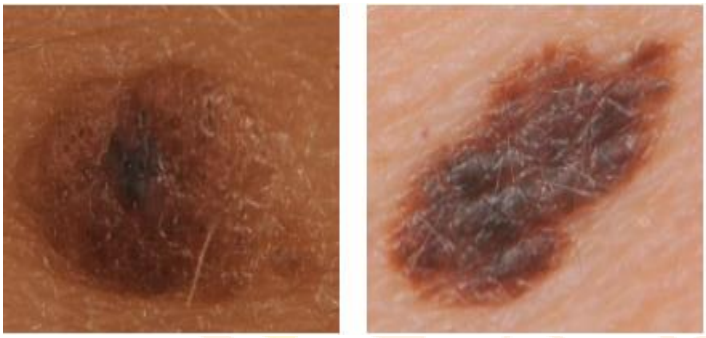

Figure 2: Naevus Mole Images

3.2 Experimental Setup

The experiments carried out in this study are performed on Google Collab Notebook cloud environment for its support for various frameworks such as TensorFlow, Keras and scikit-image [14]. It provides a 12 GB NVIDIA Tesla K80 GPU that could be used continuously for up to 12 hours and was highly integrated with Google Drive. It also offered TPU recently for free. The image processing tasks are performed by employing the use of scikit-image, nd-image and CV2 (open CV) Python libraries while the training and evaluation of our pre-trained model (VGG19) are carried out using Keras based on TensorFlow framework.

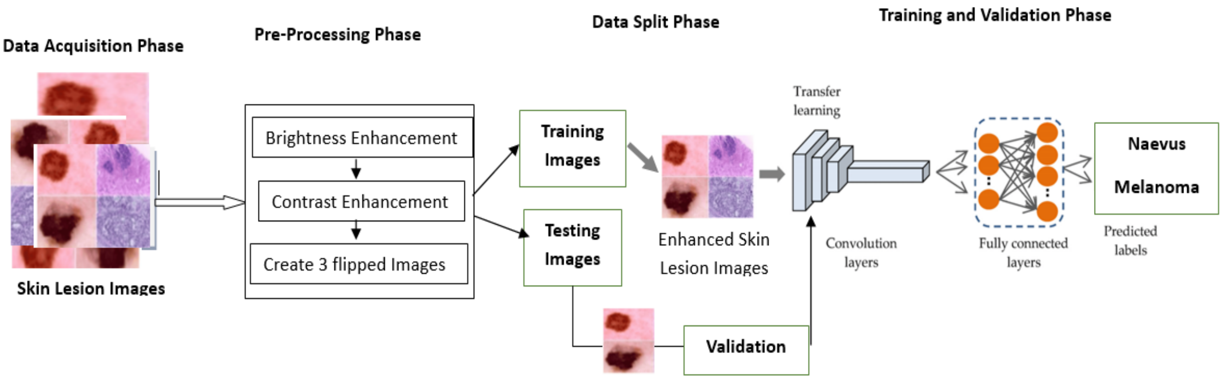

Figure 3: The methodology Adopted in this Study

3.3 Pre-processing Phase

The skin lesion images collected from the MED-NODE dataset is fed into the preprocessing phase and processed according to **Algorithm 1.** The images in this dataset are RGB (colored) images. In an RGB image, there are three channels, namely r ed (R), green (G), and blue (B), each representing a different color component. These channels combine together to create a full-color image with various intensity levels as used by Cathode-ray tubes (CRT) to represent human perception of RGB according to certain weights as described in Eqn 1.

To begin with, since the images are of different shapes and sizes, the first task of the preprocessing stage is to resize al the i mages into H_y x W_x without distorting the information contains in the image [15]. To maintain the image data, the image is left unconverted and passed to the brightness enhancement stage of the image-processing where gamma correction is perf ormed on the input image with a gamma value of 1.5 (γ=1.5) which transforms the skin lesion image pixelwise after rescaling each pixel to a range of 0-1 according to the equation in (2). The gamma correction improves the brightness of the images because the images are captured with digital camera at various light conditions. In addition to brightness enhancement, the contrast of the r esulting images is also improved by a factor 0.8.

Finally, after the images brightness and contrast are enhanced, each image is flipped right and flipped down to obtain three images comprising of the original image and two flipped images. This is to remedy the limitation in the number of images present in the d ataset which will result in poor performance for the convolutional neural network (CNN) model

$$Gim = 0.2125R + 0.7154G + 0.0721B \tag{1}$$

$$I_{out} = cI_{in}{}^{\gamma} \tag{2}$$

Where I_{out} is the output image, c is constant (normally c=1), I_{in} is input image and γ is the brightness factor.

Algorithm 1: Image Processing Algorithm

```
INPUT:
X: Skin lesion image from MED-NODE dataset
OUTPUT:
  Xen,Xen_down, Xen_right: Enhanced image, enhanced image flipped down, enhanced image flipped right
STEPS
for each X in MED-NODE Images:
     Xen ← resize_image (X, (Hy x Wx ))
     Xen ← adjust_gamma(Xen, gamma=1.5)
    Xen_down ← flip_down(Xen )
   Xen _right ← flip_right(Xen )
  Return Xen , Xen_down, Xen_right
End for
```

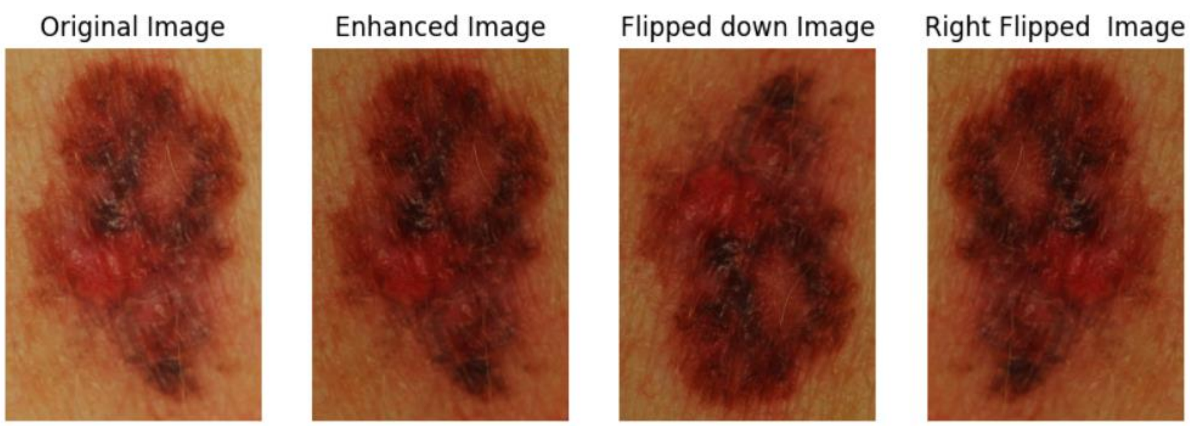

Figure 4: The Output of MED-NODE Dataset Image After Processing Using the Proposed Method

3.4 Data Split

The processed images from the previous phase are utilized in this phase for splitting into training set (80%) and testing set (20%) after data augmentation. Data augmentation is a technique employed to enhance the diversity and quantity of data available for training a model without the need to gather additional data. It involves applying various transformations and modifications to existing data samples. Common augmentation techniques include cropping, padding, flipping, zooming in and out, and altering image sizes. These techniques are utilized to expand the dataset by introducing variations in the data [16].

In the context of this study, several data augmentation techniques were employed, namely zooming in and out, flipping, and rotation. By applying these techniques to the existing data, the dataset was expanded, providing a broader range of examples for training the model. This augmentation strategy helps to improve the model's ability to generalize and perform well on unseen data.

3.5 Training and Validation Phase

Extensive research has demonstrated that a basic artificial neural network (ANN) reaches a point where it becomes inadequate, particularly when dealing with large images. This limitation often leads to overfitting issues, emphasizing the need for more advanced approaches in image classification tasks. Convolutional Neural Networks (CNNs) is a powerful class of deep neural networks that revolutionizes various domains such as; image classification and recognition, object detection, face recognition, and so on.

Unlike the traditional ANNs, CNNs offer several significant advantages in handling image data. One of their key strengths lies in their ability to automatically detect important features and extract relevant information from images, which greatly facilitates the image classification process [17],[18],[19]. This is achieved through the utilization of filters that extract features from the input images, while also utilizing pooling techniques to reduce the number of learnable parameters.

The structure of a CNN model typically encompasses five stages of neural layers: input layer, convolutional layer with rectified linear unit (ReLU) activation, pooling layer, fully connected layer, and output layer. Each stage plays a crucial role in the network's overall functionality, enabling effective feature extraction and classification.

Finally, in this phase, the proposal utilizes model that is trained on the processed skin lesion images for 10 epochs with a batch size of 32, one fully connected layer with 1028 neurons fired by ReLU activation function and an output layer; all stacked on top of VGG19 pre-trained model. The model is trained using Adam optimizer with a learning rate of 0.0001.

RESULT ANALYSIS AND DISCUSSION

The proposed Melanoma skin cancer detection system using medical image processing and transfer learning to detection between melanoma skin cancer and naevus mole is evaluated using accuracy metric given by equation (3).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \qquad (3)$$

Where TP, TN, FN and FP stand for True Positive, True Negative, False Negative, and False Positive respectively.

The results obtained from the study demonstrated the impact of image processing technique proposed in this paper as well as the use of transfer learning technique as observed in Figure 5. The accuracy obtained using a CNNs model with five (5) hidden layers on the raw skin lesion images from the MED-NODE dataset is merely better than a common guess with only approximately 67%. An improvement to an accuracy of 74.8% is recorded when the same raw data is used to train VGG19 model. This is because of the high capability of learned features extraction from the ImageNet dataset by the VGG19 model. We recorded a significant improvement in the result in term of accuracy metric (more than 10% increase in accuracy) when our pre-trained model is trained on the skin lesion images from MED-NODE dataset that are processed according to approach proposed in this paper. The validation accuracy of 85.6% demonstrates the impact of the proposed image processing technique on skin cancer detection.

Table 1 Average Training and Validation Accuracy of All the Methods

Method	Training Accuracy	Validation Accuracy
CNN only	0.6823	0.6743
VGG19 on Raw Images	0.744	0.7482
Proposed Method	**0.8457**	**0.8571**

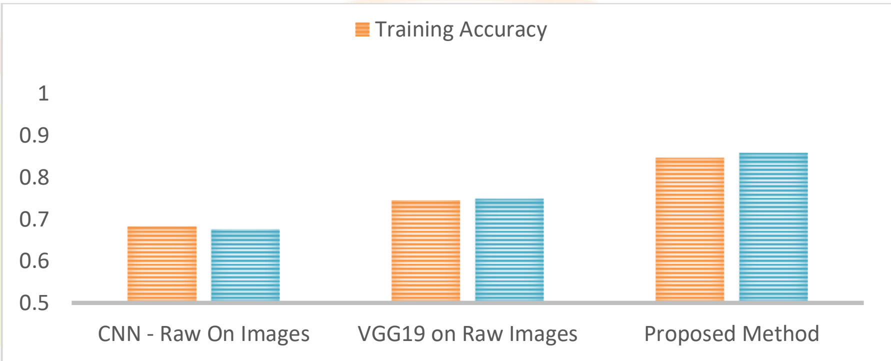

Figure 5: Comparison of Training and Validation Accuracy Between the Methods

3.1 Comparison with State-of-the-Art

The results obtained from the proposed melanoma skin cancer detection using image processing and transfer learning is further compared to some related work that utilizes the MED-NODE dataset for validation. As we can observe from TABLE 2, our proposed approach has recorded a significantly impressed accuracy compared to the works presented by the authors in 1,2,3,4. This stressed the impact of the image processing techniques employed in this study.

Table 2 Comparison With Related Works in the Literature

Ref	Accuracy
[11]	0.76
[12]	0.81
[5]	0.86

[20]	0.81
Proposed Method	**0.86**

CONCLUSION

Statistics have shown the devastating effect of melanoma skin cancer on its patients which could result in eventual loss of lives. In this paper, a novel approach is proposed for detecting melanoma skin cancer using image processing and transfer learning. The new approach demonstrates high superiority over existing works.

In the near future, more advanced and diverse dataset with images taken using CT scan, ECG etc. can be explored to further enhance the detection process of melanoma skin cancer. By so doing, it will address some limitations of the dataset used in this study, and the impact on the result obtained can be further studied.

Acknowledgment

The authors in this research appreciate the author of MED-NODE dataset.

References

[1] A. C. Society, "Key Statistics for Melanoma Skin Cancer".

[2] C. M. Shannon *et al.*, "Anatomic Region of Cutaneous Melanoma Impacts Survival and Clinical Outcomes: A Population-Based Analysis," *Cancers (Basel).*, vol. 15, no. 4, p. 1229, 2023.

[3] M. M. Vijayalakshmi, "Melanoma skin cancer detection using image processing and machine learning," *Int. J. Trend Sci. Res. Dev.*, vol. 3, no. 4, pp. 780–784, 2019.

[4] M.-A. Berciano-Guerrero, M. Guardamagna, E. Perez-Ruiz, J.-M. Jurado, I. Barragán, and A. Rueda-Dominguez, "Treatment of Metastatic Melanoma at First Diagnosis: Review of the Literature," *Life*, vol. 12, no. 9, p. 1302, 2022.

[5] S. Mukherjee, A. Adhikari, and M. Roy, "Malignant melanoma detection using multi layer perceptron with optimized network parameter selection by pso," in *Contemporary Advances in Innovative and Applicable Information Technology: Proceedings of ICCAIAIT 2018*, 2019, pp. 101–109.

[6] G. Argenziano, G. Fabbrocini, P. Carli, V. De Giorgi, E. Sammarco, and M. Delfino, "Epiluminescence microscopy for the diagnosis of doubtful melanocytic skin lesions: comparison of the ABCD rule of dermatoscopy and a new 7-point checklist based on pattern analysis," *Arch. Dermatol.*, vol. 134, no. 12, pp. 1563–1570, 1998.

[7] H. A. Idris, A. Muhammad, B. Aliyu, and S. U. Suleiman, "A Review of Explainable Artificial Intelligence : Taxonomies , Challenges , Implementation Frameworks and Future Directions," *Int. J. Eng. Res. Technol.*, vol. 12, no. 11, 2023, doi: 10.17577/IJERTV12IS120105.

[8] L. Agilandeeswari, M. T. Sagar, and N. Keerthana, "Skin lesion detection using texture based segmentation and classification by convolutional neural networks (CNN)," *Int J Innov Technol Explor. Eng*, vol. 9, pp. 2117–2120, 2019.

[9] V. Sudha and T. R. Ganeshbabu, "A Convolutional Neural Network Classifier VGG-19 Architecture for Lesion Detection and Grading in Diabetic Retinopathy Based on Deep Learning.," *Comput. Mater. \& Contin.*, vol. 66, no. 1, 2021.

[10] S. Gurung and Y. R. Gao, "Classification of Melanoma (Skin Cancer) using Convolutional Neural Network," in *2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA)*, 2020, pp. 1–8. doi: 10.1109/CITISIA50690.2020.9371829.

[11] I. Giotis, N. Molders, S. Land, M. Biehl, M. F. Jonkman, and N. Petkov, "MED-NODE: A computer-assisted melanoma diagnosis system using non-dermoscopic images," *Expert Syst. Appl.*, vol. 42, no. 19, pp. 6578–6585, 2015.

[12] E. Nasr-Esfahani *et al.*, "Melanoma detection by analysis of clinical images using convolutional neural network," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016, pp. 1373–1376.

[13] D. J. Bora, "Importance of image enhancement techniques in color image segmentation: A comprehensive and comparative study," *arXiv Prepr. arXiv1708.05081*, 2017.

[14] E. Bisong and E. Bisong, "Google colaboratory," *Build. Mach. Learn. Deep Learn. Model. google cloud Platf. a Compr. Guid. beginners*, pp. 59–64, 2019.

[15] C. Kanan and G. W. Cottrell, "Color-to-grayscale: does the method matter in image recognition?," *PLoS One*, vol. 7, no. 1, p. e29740, 2012.

[16] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *J. big data*, vol. 6, no. 1, pp. 1–48, 2019.

[17] R. Refianti, A. B. Mutiara, and R. P. Priyandini, "Classification of melanoma skin cancer using convolutional neural network," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 3, 2019.

[18] M. A. Al-Masni, M. A. Al-Antari, M.-T. Choi, S.-M. Han, and T.-S. Kim, "Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks," *Comput. Methods Programs Biomed.*, vol. 162, pp. 221–231, 2018.

[19] M. Q. Khan *et al.*, "Classification of melanoma and nevus in digital images for diagnosis of skin cancer," *IEEE Access*, vol. 7, pp. 90132–90144, 2019.

[20] S. R. S. Jianu, L. Ichim, and D. Popescu, "Automatic diagnosis of skin cancer using neural networks," in *2019 11th International Symposium on Advanced Topics in Electrical Engineering (ATEE)*, 2019, pp. 1–4.