KESATRIA: Jurnal Penerapan Sistem Informasi (Komputer & Manajemen)
Terakreditasi Nomor 204/E/KPT/2022 | Vol. 5, No. 3, Juli (2024), pp. 1328-1337

Deep Learning Techniques For Skin Cancer Detection And Diagnosis

Gagah Dwiki Putra Aryono[1], Alisa Audina[2], Sigit Auliana[3]
[1,2,3]Information Systems Department, Faculty of Computer Science, Universitas Bina Bangsa, Indonesia
E-mail: gagahdpa@gmail.com[1], alisaaaaadin000@gmail.com[2], pasigit@gmail.com[3]

Abstract

Skin cancer is the most common type of cancer globally, and early detection is crucial for effective treatment. This research reviews the use of deep learning techniques in detecting and diagnosing skin cancer. A review of current methodologies was conducted to propose new strategies for improving the accuracy and reliability of the detection and diagnosis processes. Various deep learning models, including convolutional neural networks, were evaluated using three publicly available datasets. The PSO algorithm was utilized for segmentation and feature extraction, while also exploring the impact of transfer learning, data augmentation, and model ensemble on model accuracy. The findings of this study indicate that deep learning techniques can significantly enhance the detection and diagnosis of skin cancer.

Keywords: *Skin Cancer Detection, PSO Algorithm, AlexNet, ResNet-50, VGG16*

1. Introduction

Despite being the most common type of cancer worldwide, skin cancer remains a significant cause of mortality on a global scale [1], [2]. Timely detection and diagnosis are essential for successful treatment outcomes. Recent advancements in artificial intelligence, especially deep learning, have facilitated the creation of automated techniques for detecting and diagnosing skin cancer [3]. These systems can perform medical image analysis, such as dermoscopy image analysis, and provide accurate diagnoses [4]. Deep learning employs algorithms to detect data patterns, uncovering patterns in complex datasets like images, audio, and videos. These algorithms identify patterns and make predictions from large datasets, enhancing machine intelligence [5]. As a result, deep learning has attracted considerable attention in medical imaging, where algorithms are utilized to analyze medical images and enhance the detection accuracy of skin cancer, providing more precise diagnoses. [6].

A variety of deep learning algorithms have been devised for the detection and diagnosis of skin cancer, such as support vector machines (SVMs), deep neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) [7], [8]. Each of these algorithms has its own advantages and disadvantages. SVMs, a specific type of algorithm within deep learning, can categorize data into multiple groups. Their capability to analyze intricate medical images and offer dependable diagnoses makes SVMs an outstanding choice for the detection and diagnosis of skin cancer [9].

Recent studies have demonstrated that automated systems can identify and diagnose skin cancer using medical images [10], [11]. Implementing these algorithms has the potential to enhance diagnostic accuracy and efficiency, thereby improving overall clinical outcomes for patients. [12]. This is particularly important as early detection of skin cancer can significantly enhance the effectiveness of treatment, potentially saving lives [13], [14].

Deep learning's ability to handle large datasets, including high-resolution medical images, makes it a powerful tool in combating skin cancer. CNNs, specifically designed for pixel data processing, have proven highly effective in analyzing dermoscopy images. [15]. CNNs can

ISSN: 2720-992X

learn to identify patterns and features that indicate skin cancer from extensive image data, resulting in highly accurate diagnostic outcomes [16].

Additionally, deep learning methods like transfer learning, data augmentation, and model ensemble boost the accuracy of these systems. Transfer learning, for instance, uses a pre-trained model for a related problem, saving time and computational resources while enhancing performance [17]. Data augmentation techniques, which generate additional training data from existing data, help in creating more robust models by reducing overfitting. Model ensemble, which combines predictions from multiple models, often leads to improved accuracy compared to using a single model [18].

Previous studies have used deep learning techniques to detect and diagnose skin cancer. For example, an intelligent Region of Interest (ROI) system based on transfer learning was developed to distinguish melanoma from benign nevi. The system employed an updated k-means method to extract images into ROIs, which were then used to train a CNN-based transfer learning model. Data augmentation was applied to ROI images sourced from DermIS and DermQuest datasets to identify discriminative features from melanoma-only images [19]. Melanoma detection from cutaneous lesions was explored, focusing on pre-processing and segmentation of skin lesion images. The study compared existing technologies and addressed categorization methods for classifying skin lesions into skin cancer categories [20]. The use of three methods for prediction: two traditional deep learning classifiers and a convolutional neural network trained on skin lesion boundaries, texture, and color. These methods are integrated via majority voting to enhance their results. Testing has demonstrated that maximum accuracy is achieved when all three approaches are used concurrently. An integrated deep feature fusion approach for skin cancer detection was introduced, where AlexNet and VGG-16 extract features from segmented skin lesion images and combine them for classification [21]. A thorough review of deep learning methods for early detection of skin cancer was conducted by analyzing several high-quality research papers. The study revealed that CNNs outperform other neural network types in image data identification due to their direct association with computer vision. [22].

Despite advancements in deep learning for skin cancer detection, challenges like limited dataset generalization and scalability remain. This study uses ensemble learning to improve detection accuracy and compares its method with previous approaches.

2. Research Methodology

The primary objective of this work is to identify images of skin cancer using VGG16 architecture, while also comparing the performance to AlexNet and ResNet-50. Image pre-processing techniques, including morphological image processing and the Hough transform, were utilized.

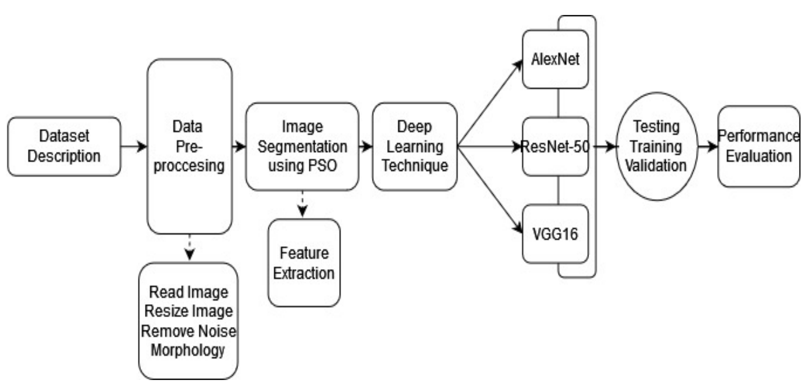

Figure 1. Research Stage

Based on Figure 1, the explanation for each stage is as follows:

2.1. Dataset Description

This research uses the HAM10000 dataset from Kaggle, featuring 10,015 dermatoscopic images of diverse skin lesions for dermatology studies [23]. Accompanied by metadata including diagnosis type, patient age, gender, and lesion location, the images are stored in JPG format with unique identifiers, while CSV files contain corresponding metadata and labels for easy mapping and utilization in training and evaluating machine learning algorithms for automated skin cancer diagnosis [24].

2.2. Data Pre-processing

In image classification pre-processing, various methods are applied sequentially to enhance accuracy in basic convolutional networks [25]. Initially, images are read into memory by storing their file paths and using programming functions for loading. Resizing methods are then employed to display and compare images, facilitating size transformation for uniform processing. Gaussian blur, a widely used technique in graphics, effectively reduces noise and enhances image quality by convolving with a Gaussian kernel. Morphological operations further refine images by manipulating pixel structures using predefined shapes, enhancing features, segmenting objects, and preparing images for subsequent computer vision tasks with improved clarity and interpretability [26].\

2.3. Image Segmentation using PSO

Image segmentation using Particle Swarm Optimization (PSO) is a method where the goal is to partition an image into meaningful segments or regions. This preprocessing step is crucial for tasks like pattern recognition and feature extraction in image processing [27]. This iterative process aims to find an optimal segmentation that divides the skin images into background and foreground regions effectively. PSO's ability to explore and exploit search spaces makes it useful for extracting relevant features from images, enhancing subsequent analysis and classification tasks in computer vision [28]. The PSO formula updates particle positions and velocities based on their own experiences and the best experiences of their neighbors [29], [30]:

Update Velocity

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 \left(P_{i,best}^t - X_i^t\right) + c_2 r_2 \left(G_{i,best}^t - X_i^t\right) \quad (1)$$

where:

V_i^t is the velocity of particle i at iteration t.

ω is the inertia weight, controlling the impact of the previous velocity.

c_1 and c_2 are acceleration coefficients (cognitive and social components, respectively).

r_1 and r_2 are random numbers uniformly distributed in $[0,1]$.

$P_{i,best}^t$ is the best position (fitness) of particle i up to iteration t.

$G_{i,best}^t$ is the best position (fitness) among all particles in the swarm up to iteration t.

Update Position

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (2)$$

where:

X_i^t is the current position of particle i at iteration t.

X_i^{t+1} is the updated position of particle i at iteration $t+1$.

PSO iteratively updates particle positions and velocities to find optimal solutions, efficiently exploring the search space using individual and swarm knowledge, making it effective for optimization tasks like image segmentation and feature extraction [31].

2.4. Deep Learning Technique

In this section, the Background of Skin Cancer outlines the architecture of the existing models, AlexNet and ResNet-50, as well as our proposed model, VGG16.

a) AlexNet

The architecture has eight layers: five convolutional and three fully connected. Convolutional layers use overlapping max-pooling, and all outputs are connected to the ReLU activation function [32].

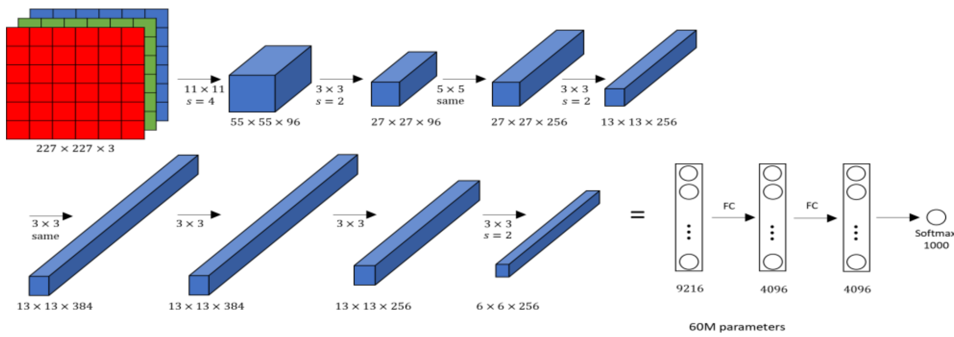

Figure 2. AlexNet Architecture

A SoftMax activation layer in AlexNet provides a distribution of 1,000 class labels. AlexNet processes 256x256 RGB images with 650,000 neurons and 60 million parameters. Dropout layers in the first two fully connected layers prevent overfitting. [33].

b) ResNet-50

Microsoft's ResNet-50, a 50-layer CNN, uses residual blocks with shortcut connections to enhance image classification accuracy. Each residual block has three convolutional layers with direct input links. [34]. ResNet-50's shortcut connections allow deeper, more complex feature learning. Using batch normalization and ReLU activation, it excels in image classification, object detection, and segmentation. Its state-of-the-art performance on benchmarks like ImageNet makes it ideal for transfer learning in computer vision. [35].

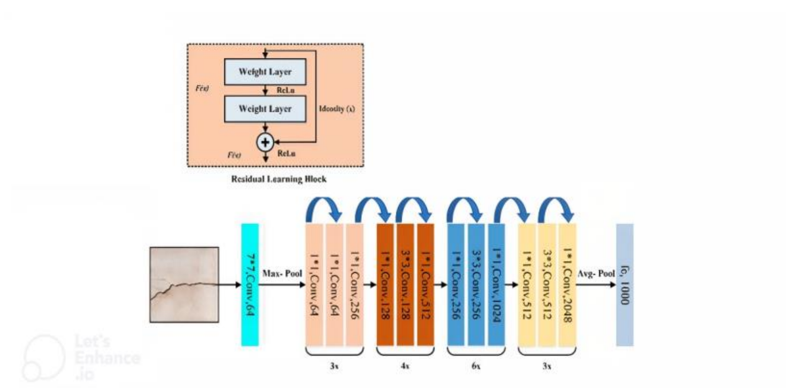

Figure 3. ResNet-50 Architecture

c) VGG16

VGG16, developed by Andrew Zisserman and Karen Simonyan at Oxford, marked a significant milestone in computer vision. Conceptualized in 2013, it was finalized for the 2014 ILSVRC ImageNet Challenge.[36]. The ILSVRC is an annual competition evaluating large-scale image classification and object detection techniques.

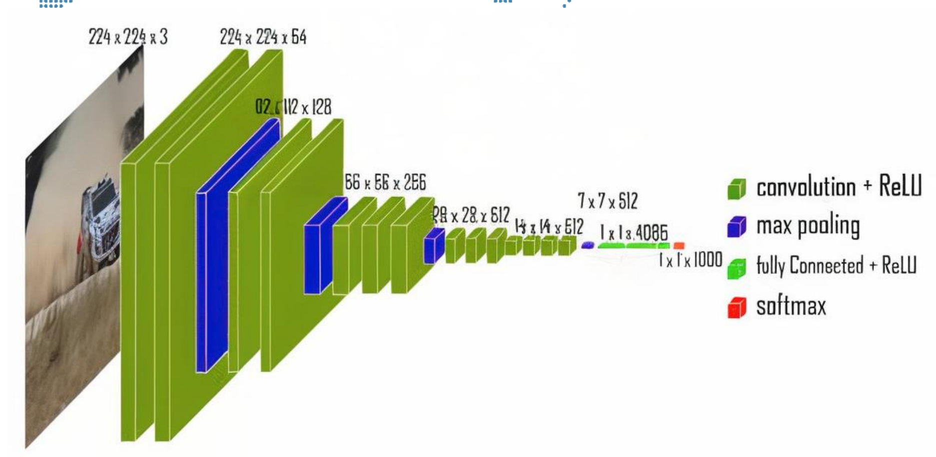

Figure 4. VGG16 Architecture

2.5. Model Training, Validation and Testing

Model training, validation, and testing are crucial for ensuring the effectiveness and reliability of deep learning models for skin cancer detection and diagnosis [37]. During training, models like VGG16, ResNet-50, or AlexNet are trained on labeled datasets such as HAM10000, adjusting weights to minimize prediction error [38]. Validation involves evaluating the model on a separate set to tune hyperparameters and prevent overfitting [39]. Finally, testing assesses the model's performance on an independent test set, providing an objective measure of accuracy, precision, and recall [40]. These steps ensure the model's robustness and reliability in clinical applications.

3. Results and Discussion

3.1. Experimental Results

Recent research shows promising results using deep learning for skin cancer detection. This study evaluates models like VGG16, ResNet-50, and AlexNet, trained on the diverse HAM10000 dataset to identify various skin lesions accurately. [41]. The models' results are compared by accuracy, precision, recall, and other metrics to find the best approach.

This chapter presents our experimental findings, analyzing deep learning model performance with pre-processing steps like resizing, noise removal, and morphological processing. We also explore PSO segmentation's impact, comparing results with existing methods and identifying potential research areas.

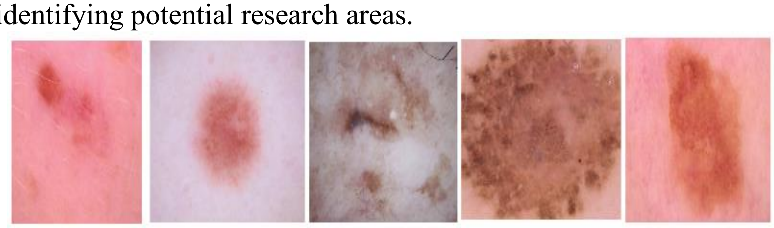

Figure 5. Skin Cancer Dataset

Image segmentation groups pixels with similar texture, color, and form into units, crucial for feature extraction, selection, and classification. Effective segmentation is vital in dermoscopy images due to varying lesion sizes, colors, and artifacts like hairs. Our strategy aims to develop an automatic segmentation method for lesion detection, using PSO algorithms to minimize the energy function. This method involves artificial particles optimizing the class label for each pixel, resulting in various potential clustering options. The segmentation results are shown in the figure.

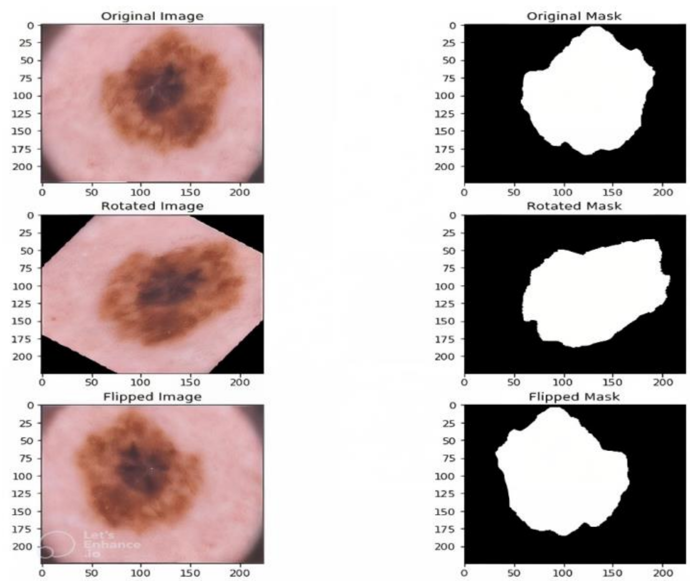

Figure 6. Skin Lesion Segmentation Using PSO

Figure 6 illustrates image augmentation techniques for medical imaging. The left column shows a skin lesion image in three states: original, rotated, and flipped. The right column displays corresponding binary masks, which highlight the lesion area for each image state. Augmentation helps increase the dataset's diversity, improving machine learning model robustness and accuracy. Rotation and flipping are common methods that change the image's orientation without altering its essential features, preserving the lesion's shape and size in the mask. This approach enhances the model's ability to generalize from varied input data.

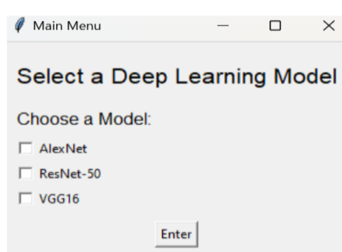

Figure 7. Framework of Proposed System

Figure 7 depicts a graphical user interface (GUI) titled 'Select a Deep Learning Model' featuring three checkboxes for choosing pre-trained models: AlexNet, ResNet-50, and VGG16. Below these options, there is an 'Enter' button to submit the selection. These models are widely utilized in image recognition tasks."

3.2. Performance Evaluation

Performance metrics such as accuracy, sensitivity, precision, and specificity are crucial in evaluating the effectiveness of techniques, as shown in the confusion matrix. These metrics collectively provide a comprehensive view of how well a technique performs in its classification tasks, aiding in informed decision-making and model optimization [42].

a. Accuracy

It represents the proportion of subjects correctly identified among all subjects.

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

b. Sensitivity

The recall, or sensitivity, denotes the percentage of correctly identified positive labels by our computer system.

$$Sensitivity = \frac{TP}{TP+FN} \quad (4)$$

c. Precision

Considering the total number of accurate predictions, we can ascertain the reliability of a forecast, also known as predictive value.

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

d. Specificity

The algorithm's correct classification of negatives is referred to as specificity within the realm of performance evaluation metrics.

$$Specificity = \frac{TN}{TN+FP} \quad (6)$$

The test results using AlexNet and ResNet-50, as well as our proposed model, VGG16, are shown in the table 1 below.

Table 1. Performance Results

Architectures	Accuracy (%)	Specificity (%)	Sensitivity (%)	Precision (%)
VGG16	93.24	80.61	93.24	88.95
ResNet-50	88.5	83.29	85.47	84.65
AlexNet	86.21	89.98	78.36	81.01

Table 1 presents performance metrics for three different convolutional neural network (CNN) architectures—VGG16, ResNet-50, and AlexNet—evaluated on some tasks, presumably a classification or detection problem. VGG16 achieved the highest accuracy at 93.24%, indicating its effectiveness in correctly predicting outcomes overall. It also showed a high sensitivity (93.24%), suggesting a strong ability to correctly identify positive instances (true positives) relative to all actual positives. However, its specificity (80.61%) indicates a moderate ability to correctly identify negative instances (true negatives). ResNet-50 followed with an accuracy of 88.5%, showing slightly lower overall performance than VGG16 but with better specificity (83.29%). This suggests ResNet-50 is better at correctly identifying negatives, though slightly less sensitive than VGG16. AlexNet, while achieving an accuracy of 86.21%, had the highest specificity (89.98%), indicating strong performance in correctly identifying negatives, but lower sensitivity (78.36%), indicating it may miss some positive instances.

4. Conclusion

In this study, we developed a CNN architecture based on VGG16 for skin cancer detection. We used pre-processed data to train our model on the training set and evaluated it using the test set. We also employed AlexNet and ResNet-50 to assess and compare the performance of our proposed VGG16 model. The results indicate that the VGG16 model is the most robust for skin cancer detection, especially when high sensitivity is crucial. The implications of this research are significant for medical diagnostics, as accurately identifying positive cases of skin cancer is critical for early treatment and improved patient outcomes. This research suggests that using VGG16 could enhance diagnostic accuracy, potentially leading to better clinical decision-making and patient care.

References

[1] K. Urban, S. Mehrmal, P. Uppal, R. L. Giesey, and G. R. Delost, “The global burden of skin cancer: A longitudinal analysis from the Global Burden of Disease Study, 1990–2017,” *JAAD Int.*, vol. 2, pp. 98–108, Mar. 2021, doi: 10.1016/j.jdin.2020.10.013.

[2] E. R. Parker, “The influence of climate change on skin cancer incidence – A review of the evidence,” *Int. J. Women’s Dermatology*, vol. 7, no. 1, pp. 17–27, Jan. 2021, doi: 10.1016/j.ijwd.2020.07.003.

[3] J. Shao, J. Feng, J. Li, S. Liang, W. Li, and C. Wang, “Novel tools for early diagnosis and precision treatment based on artificial intelligence,” *Chinese Med. J. Pulm. Crit. Care Med.*, vol. 1, no. 3, pp. 148–160, Sep. 2023, doi: 10.1016/j.pccm.2023.05.001.

[4] D. Painuli, S. Bhardwaj, and U. Köse, “Recent advancement in cancer diagnosis using machine learning and deep learning techniques: A comprehensive review,” *Comput. Biol. Med.*, vol. 146, p. 105580, Jul. 2022, doi: 10.1016/j.compbiomed.2022.105580.

[5] I. H. Sarker, “Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions,” *SN Comput. Sci.*, vol. 2, no. 6, p. 420, Nov. 2021, doi: 10.1007/s42979-021-00815-1.

[6] X. Chen *et al.*, “Recent advances and clinical applications of deep learning in medical image analysis,” *Med. Image Anal.*, vol. 79, p. 102444, Jul. 2022, doi: 10.1016/j.media.2022.102444.

[7] L. Wang, “Deep Learning Techniques to Diagnose Lung Cancer,” *Cancers (Basel).*, vol. 14, no. 22, p. 5569, Nov. 2022, doi: 10.3390/cancers14225569.

[8] K. A. Tran, O. Kondrashova, A. Bradley, E. D. Williams, J. V. Pearson, and N. Waddell, “Deep learning in cancer diagnosis, prognosis and treatment selection,” *Genome Med.*, vol. 13, no. 1, p. 152, Dec. 2021, doi: 10.1186/s13073-021-00968-x.

[9] A. Zadeh Shirazi, M. Tofighi, A. Gharavi, and G. A. Gomez, “The Application of Artificial Intelligence to Cancer Research: A Comprehensive Guide,” *Technol. Cancer Res. Treat.*, vol. 23, Jan. 2024, doi: 10.1177/15330338241250324.

[10] E. Rezk, M. Haggag, M. Eltorki, and W. El-Dakhakhni, “A comprehensive review of artificial intelligence methods and applications in skin cancer diagnosis and treatment: Emerging trends and challenges,” *Healthc. Anal.*, vol. 4, p. 100259, Dec. 2023, doi: 10.1016/j.health.2023.100259.

[11] A. Shah *et al.*, “A comprehensive study on skin cancer detection using artificial neural network (ANN) and convolutional neural network (CNN),” *Clin. eHealth*, vol. 6, pp. 76–84, Dec. 2023, doi: 10.1016/j.ceh.2023.08.002.

[12] A. Takiddin, J. Schneider, Y. Yang, A. Abd-Alrazaq, and M. Househ, “Artificial Intelligence for Skin Cancer Detection: Scoping Review,” *J. Med. Internet Res.*, vol. 23, no. 11, p. e22934, Nov. 2021, doi: 10.2196/22934.

[13] D. Raval and J. N. Undavia, “A Comprehensive assessment of Convolutional Neural Networks for skin and oral cancer detection using medical images,” *Healthc. Anal.*, vol. 3, p. 100199, Nov. 2023, doi: 10.1016/j.health.2023.100199.

[14] S. Nazari and R. Garcia, “Automatic Skin Cancer Detection Using Clinical Images: A

Comprehensive Review," *Life*, vol. 13, no. 11, p. 2123, Oct. 2023, doi: 10.3390/life13112123.

[15] S. Indolia, A. K. Goswami, S. P. Mishra, and P. Asopa, "Conceptual Understanding of Convolutional Neural Network- A Deep Learning Approach," *Procedia Comput. Sci.*, vol. 132, pp. 679–688, 2018, doi: 10.1016/j.procs.2018.05.069.

[16] M. M. Taye, "Theoretical Understanding of Convolutional Neural Network: Concepts, Architectures, Applications, Future Directions," *Computation*, vol. 11, no. 3, p. 52, Mar. 2023, doi: 10.3390/computation11030052.

[17] J. Su, X. Yu, X. Wang, Z. Wang, and G. Chao, "Enhanced transfer learning with data augmentation," *Eng. Appl. Artif. Intell.*, vol. 129, p. 107602, Mar. 2024, doi: 10.1016/j.engappai.2023.107602.

[18] B. Li, Y. Hou, and W. Che, "Data augmentation approaches in natural language processing: A survey," *AI Open*, vol. 3, pp. 71–90, 2022, doi: 10.1016/j.aiopen.2022.03.001.

[19] K. M. Hosny, M. A. Kassem, and M. M. Foaud, "Skin melanoma classification using ROI and data augmentation with deep convolutional neural networks," *Multimed. Tools Appl.*, vol. 79, no. 33–34, pp. 24029–24055, Sep. 2020, doi: 10.1007/s11042-020-09067-2.

[20] A. Adegun and S. Viriri, "Deep learning techniques for skin lesion analysis and melanoma cancer detection: a survey of state-of-the-art," *Artif. Intell. Rev.*, vol. 54, no. 2, pp. 811–841, Feb. 2021, doi: 10.1007/s10462-020-09865-y.

[21] M. S. Ali, M. S. Miah, J. Haque, M. M. Rahman, and M. K. Islam, "An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models," *Mach. Learn. with Appl.*, vol. 5, p. 100036, Sep. 2021, doi: 10.1016/j.mlwa.2021.100036.

[22] M. Dildar *et al.*, "Skin Cancer Detection: A Review Using Deep Learning Techniques," *Int. J. Environ. Res. Public Health*, vol. 18, no. 10, p. 5479, May 2021, doi: 10.3390/ijerph18105479.

[23] K. Ali, Z. A. Shaikh, A. A. Khan, and A. A. Laghari, "Multiclass skin cancer classification using EfficientNets – a first step towards preventing skin cancer," *Neurosci. Informatics*, vol. 2, no. 4, p. 100034, Dec. 2022, doi: 10.1016/j.neuri.2021.100034.

[24] P. Tschandl, C. Rosendahl, and H. Kittler, "The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions," *Sci. Data*, vol. 5, no. 1, p. 180161, Aug. 2018, doi: 10.1038/sdata.2018.161.

[25] M. Salvi, U. R. Acharya, F. Molinari, and K. M. Meiburger, "The impact of pre- and post-image processing techniques on deep learning frameworks: A comprehensive review for digital pathology image analysis," *Comput. Biol. Med.*, vol. 128, p. 104129, Jan. 2021, doi: 10.1016/j.compbiomed.2020.104129.

[26] R. A. Lotufo, R. Audigier, A. V. Saúde, and R. C. Machado, "Morphological Image Processing," in *Microscope Image Processing*, Elsevier, 2023, pp. 75–117. doi: 10.1016/B978-0-12-821049-9.00012-5.

[27] X. Song and H. Li, "Segmentation Based on Particle Swarm Optimization," 2021, pp. 731–736. doi: 10.1007/978-3-030-53980-1_107.

[28] J. C. Canales, J. C. Canales, F. García-Lamont, A. Yee-Rendon, J. S. R. Castilla, and L. R. Mazahua, "Optimal segmentation of image datasets by genetic algorithms using color spaces," *Expert Syst. Appl.*, vol. 238, p. 121950, Mar. 2024, doi: 10.1016/j.eswa.2023.121950.

[29] L. Xu, B. Song, and M. Cao, "An improved particle swarm optimization algorithm

with adaptive weighted delay velocity," *Syst. Sci. Control Eng.*, vol. 9, no. 1, pp. 188–197, Jan. 2021, doi: 10.1080/21642583.2021.1891153.

[30] F. Marini and B. Walczak, "Particle swarm optimization (PSO). A tutorial," *Chemom. Intell. Lab. Syst.*, vol. 149, pp. 153–165, Dec. 2015, doi: 10.1016/j.chemolab.2015.08.020.

[31] S. Tijjani, M. N. Ab Wahab, and M. H. Mohd Noor, "An enhanced particle swarm optimization with position update for optimal feature selection," *Expert Syst. Appl.*, vol. 247, p. 123337, Aug. 2024, doi: 10.1016/j.eswa.2024.123337.

[32] X. Zhang, "Convolutional Neural Networks and Architectures," in *Handbook of Face Recognition*, Cham: Springer International Publishing, 2024, pp. 37–65. doi: 10.1007/978-3-031-43567-6_2.

[33] I. Singh, G. Goyal, and A. Chandel, "AlexNet architecture based convolutional neural network for toxic comments classification," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 9, pp. 7547–7558, Oct. 2022, doi: 10.1016/j.jksuci.2022.06.007.

[34] A. Deshpande, V. V. Estrela, and P. Patavardhan, "The DCT-CNN-ResNet50 architecture to classify brain tumors with super-resolution, convolutional neural network, and the ResNet50," *Neurosci. Informatics*, vol. 1, no. 4, p. 100013, Dec. 2021, doi: 10.1016/j.neuri.2021.100013.

[35] M. B. Hossain, S. M. H. S. Iqbal, M. M. Islam, M. N. Akhtar, and I. H. Sarker, "Transfer learning with fine-tuned deep CNN ResNet50 model for classifying COVID-19 from chest X-ray images," *Informatics Med. Unlocked*, vol. 30, p. 100916, 2022, doi: 10.1016/j.imu.2022.100916.

[36] A. Alshammari, "Construction of VGG16 Convolution Neural Network (VGG16_CNN) Classifier with NestNet-Based Segmentation Paradigm for Brain Metastasis Classification," *Sensors*, vol. 22, no. 20, p. 8076, Oct. 2022, doi: 10.3390/s22208076.

[37] M. K. Monika, N. Arun Vignesh, C. Usha Kumari, M. N. V. S. S. Kumar, and E. L. Lydia, "Skin cancer detection and classification using machine learning," *Mater. Today Proc.*, vol. 33, pp. 4266–4270, 2020, doi: 10.1016/j.matpr.2020.07.366.

[38] G. Algan and I. Ulusoy, "Image classification with deep learning in the presence of noisy labels: A survey," *Knowledge-Based Syst.*, vol. 215, p. 106771, Mar. 2021, doi: 10.1016/j.knosys.2021.106771.

[39] I. D. Dinov, "Model Performance Assessment, Validation, and Improvement," 2023, pp. 477–531. doi: 10.1007/978-3-031-17483-4_9.

[40] G. Naidu, T. Zuva, and E. M. Sibanda, "A Review of Evaluation Metrics in Machine Learning Algorithms," 2023, pp. 15–25. doi: 10.1007/978-3-031-35314-7_2.

[41] B. Shetty, R. Fernandes, A. P. Rodrigues, R. Chengoden, S. Bhattacharya, and K. Lakshmanna, "Skin lesion classification of dermoscopic images using machine learning and convolutional neural network," *Sci. Rep.*, vol. 12, no. 1, p. 18134, Oct. 2022, doi: 10.1038/s41598-022-22644-9.

[42] O. Rainio, J. Teuho, and R. Klén, "Evaluation metrics and statistical tests for machine learning," *Sci. Rep.*, vol. 14, no. 1, p. 6086, Mar. 2024, doi: 10.1038/s41598-024-56706-x.