



# Ai Based Skin Disease Diagnostic System

Adhithya Lp, Harish A.T, Madhan.A, Lakshmi Roopa

Dept. Of Computer Science and Business Systems Jerusalem College of Engineering Chennai, India

**Abstract** - Skin diseases represent a significant global health concern due to their increasing prevalence and the limited availability of dermatology specialists, particularly in resource- constrained regions. Early and accurate diagnosis plays a crucial role in improving treatment outcomes and reducing disease progression. This paper presents an AI-Based Skin Disease Diagnostic System that leverages deep learning and transfer learning techniques for automated skin disease classification. The proposed system employs the MobileNetV2 architecture, chosen for its computational efficiency and strong performance on image classification tasks, making it suitable for real-world deployment. The model is trained and evaluated using the HAM10000 dataset, consisting of dermatoscopic images spanning seven different skin disease classes. Image preprocessing and data augmentation techniques are applied to improve generalization and robustness. The system achieves an overall classification accuracy of 78%, demonstrating its potential as a clinical decision-support tool. The proposed solution is implemented using TensorFlow and deployed via a Streamlit-based web interface for interactive usage. Ethical considerations are emphasized, and the system is explicitly designed as a supportive diagnostic aid, not a replacement for professional dermatologists.

**Keywords** - Skin Disease Classification, Deep Learning, MobileNetV2, Transfer Learning, HAM10000 Dataset, Medical Image Analysis.

## I. INTRODUCTION

Skin diseases affect millions of individuals worldwide and range from benign conditions to life-threatening malignancies such as melanoma. Accurate diagnosis often depends on expert visual assessment and dermoscopic examination, which may not be readily available in all healthcare settings [1], [2]. The increasing demand for dermatological services has motivated the development of automated diagnostic systems to assist clinicians and patients [21], [34]. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in medical image analysis and skin lesion classification tasks [17], [21].

However, many state-of-the-art models require high computational resources, limiting their deployment in real- world applications [35], [36]. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in medical analysis and skin lesion classification tasks.[17],[21].

## II BACKGROUND AND MOTIVATION

The diagnosis of skin diseases often requires specialized medical expertise and access to dermatoscopic equipment. In developing regions and rural healthcare settings, these resources are frequently unavailable, leading to delayed diagnosis and improper treatment. Automated by providing diagnostic systems can help bridge this gap by assisting healthcare providers and patients with preliminary assessments.

**The motivation behind this work is threefold:**

- To develop an efficient and accurate skin disease classification system.
- To utilize a lightweight deep learning model suitable for deployment on standard computing devices.
- To create an accessible web-based interface that enables real-time interaction.



The availability of large, annotated medical image datasets such as HAM10000 has further enabled the development of robust AI-based diagnostic systems. However, challenges such as class imbalance, visual similarity between diseases, and overfitting remain significant. This research addresses these challenges through data preprocessing, augmentation, and transfer learning strategies. Finally, the motivation extends beyond technical innovation to social impact. By democratizing access to preliminary dermatological assessments the system has the potential to reduce healthcare disparities, empower patients in underserved regions and contribute to early detection of serious conditions such as melanoma.

The increasing prevalence of skin related diseases are the limited availability of dermatological experts highlight the need for automated diagnostic assistance. Early detection of skin conditions significantly improves treatment outcomes and reduces healthcare costs. However, manual diagnosis is often time-consuming and subject to inter-observer variability.

### III RELATED WORK

Several studies have explored the use of deep learning techniques for automated skin disease detection. Early approaches primarily utilized traditional machine learning methods combined with handcrafted features. With the emergence of CNNs, end-to-end learning frameworks have significantly improved classification accuracy.

Codella et al. demonstrated the effectiveness of deep CNN architectures in melanoma detection using dermatoscopic images. Subsequent research explored architectures such as VGGNet, ResNet, and Inception for multi-class skin disease classification. While these models achieved high accuracy, their computational complexity limited practical deployment.

Recent studies have highlighted the advantages of lightweight architectures such as MobileNet and EfficientNet for medical image analysis. These models balance performance and efficiency, making them suitable for mobile and web-based healthcare applications. Building upon this line of research, the proposed system adopts MobileNetV2 to achieve efficient and reliable skin disease classification.

### IV. PROPOSED WORK

The proposed AI-based skin disease diagnostic system aims to classify dermatoscopic images into seven predefined disease categories using a deep learning framework. The system integrates image preprocessing, transfer learning, and a web-based interface to deliver an end-to-end diagnostic solution.

#### **The key contributions of this work include:**

- Implementation of a MobileNetV2-based classification model using transfer learning.
- Use of the HAM10000 dataset for multi-class skin disease classification.
- Deployment of the trained model through a Streamlit-based interactive web application.
- Inclusion of ethical considerations to ensure responsible AI usage in healthcare.



## V. METHODOLOGY

### Dataset Description

The system utilizes the HAM10000 (Human Against Machine with 10,000 training images) dataset, a widely used benchmark dataset for skin lesion analysis. The dataset contains dermatoscopic images categorized into seven skin disease classes:

Actinic Keratoses (akiec), Basal Cell Carcinoma (bcc), Benign Keratosis-like Lesions (bkl), Dermatofibroma (df), Melanoma (mel), Melanocytic Nevi (nv), and Vascular Lesions (vasc).

Figure 1: Sample images from the HAM10000 dataset

	A	B	C	D	E	F	G
1	lesion_id	image_id	dx	dx_type	age	sex	localization
2	HAM_0000118	ISIC_0027419	bkl	histo	80	male	scalp
3	HAM_0000118	ISIC_0025030	bkl	histo	80	male	scalp
4	HAM_0002730	ISIC_0026769	bkl	histo	80	male	scalp
5	HAM_0002730	ISIC_0025661	bkl	histo	80	male	scalp
6	HAM_0001466	ISIC_0031633	bkl	histo	75	male	ear
7	HAM_0001466	ISIC_0027850	bkl	histo	75	male	ear
8	HAM_0002761	ISIC_0029176	bkl	histo	60	male	face
9	HAM_0002761	ISIC_0029068	bkl	histo	60	male	face
10	HAM_0005132	ISIC_0025837	bkl	histo	70	female	back
11	HAM_0005132	ISIC_0025209	bkl	histo	70	female	back
12	HAM_0001396	ISIC_0025276	bkl	histo	55	female	trunk
13	HAM_0001396	ISIC_0029196	bkl	histo	55	female	trunk

### Data Preprocessing

Prior to training, all images are resized to 224×224 pixels match the input requirements of MobileNetV2. Pixel values are normalized to improve convergence during training. To reduce overfitting and address class imbalance, data augmentation techniques such as rotation, horizontal flipping, and zooming are applied.

### Model Architecture

MobileNetV2 is employed as the base model due to its efficient architecture based on depthwise separable convolutions and inverted residual blocks. Pre-trained ImageNet weights are used to initialize the model, enabling effective feature extraction. Custom fully connected layers are appended to adapt the model for seven-class skin disease classification.

### Implementation Details

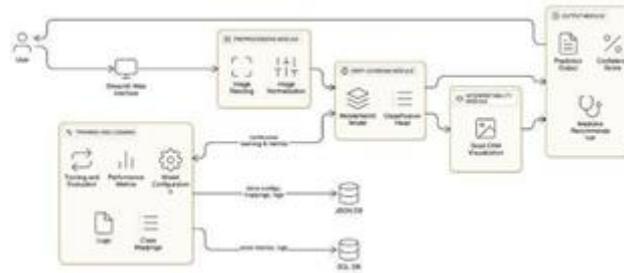
The system is implemented using TensorFlow and Keras. The base layers of MobileNetV2 are initially frozen to preserve learned features, followed by fine-tuning of selected layers. The model is trained using a categorical cross-entropy loss function and optimized using the Adam optimizer. Training is conducted in a Jupyter Notebook environment, and the final model is integrated into a Streamlit application for deployment.

### System Architecture

The overall architecture of the proposed AI-Based Skin Disease Diagnostic System is designed as a modular and scalable pipeline that integrates image acquisition, preprocessing, deep learning-based classification, and result visualization.



Figure 2: System Architecture of the Proposed AI-Based Skin Disease Diagnostic System



### Input Module

The input module serves as the primary interaction point between the user and the system. Users upload dermatoscopic skin images through a Streamlit-based web interface. This interface ensures ease of use and accessibility across standard computing devices. Uploaded images are validated and forwarded to the preprocessing module for further analysis. The web interface also facilitates real-time interaction and result visualization.

### Pre-processing Module

The preprocessing module prepares raw input images for effective deep learning inference. Images are resized to a fixed resolution compatible with the MobileNetV2 input requirements. Pixel intensity normalization is applied to standardize the image data and improve training stability. These preprocessing steps ensure consistent input quality and reduce the impact of noise and illumination variations.

### Training and Logging Module

The training and logging module is responsible for model training, evaluation, and performance monitoring. During training, the system computes key performance metrics such as accuracy, loss, and class-wise evaluation scores. Model configurations, class mappings, and hyperparameters are stored in a JSON-based database, while training logs and evaluation metrics are maintained in an SQL database. This modular logging mechanism supports continuous learning, experiment tracking, and reproducibility.

### Deep Learning Module

The deep learning module constitutes the core of the diagnostic system. It employs the MobileNetV2 architecture with transfer learning to extract discriminative features from dermatoscopic images. Pre-trained ImageNet weights are utilized to accelerate convergence and improve generalization. A custom classification head is appended to the base network to perform multi-class classification across seven skin disease categories. This lightweight architecture ensures computational efficiency while maintaining reliable diagnostic performance.

### Interpretability Module

To enhance model transparency and clinical trust, an interpretability module is integrated into the system. Gradient-weighted Class Activation Mapping (Grad-CAM) is used to generate visual explanations highlighting image regions that contribute most to the predicted class. These visualizations assist users and healthcare professionals in understanding the model's decision-making process, thereby improving interpretability and ethical acceptability.

### Output Module

The output module delivers the final diagnostic results to the user. It displays the predicted skin disease class along with a confidence score indicating the model's certainty. Additionally, supportive medical



recommendations are provided to guide users toward professional consultation. The system is explicitly designed as a decision-support tool and not a replacement for dermatologists, reinforcing responsible AI usage in healthcare applications.

## Training and Testing

### Training Process

The model training process follows a supervised learning approach using labeled images from the HAM10000 dataset. The dataset is split into training and testing subsets to evaluate generalization performance. Data augmentation techniques are applied during training to improve robustness and reduce overfitting.

Transfer learning is employed by initializing MobileNetV2 with ImageNet pre-trained weights. Initially, the base layers are frozen to retain learned generic features, while custom classification layers are trained. Fine-tuning is later performed on selected layers to adapt the model more effectively to dermatological image features.

### Testing and Evaluation

During testing, unseen images are passed through the trained model to evaluate classification accuracy. Performance metrics such as overall accuracy and class-wise prediction behavior are analyzed.

Figure 3: Training and Validation Accuracy Curve  
Transfer Learning Accuracy

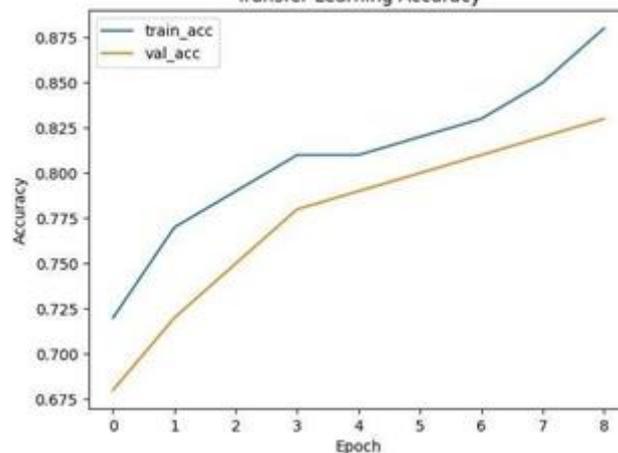


Fig. 3 illustrates the training and validation accuracy across multiple epochs. The close alignment between both curves indicates effective learning and minimal overfitting. The gradual improvement and stabilization of validation accuracy demonstrate the robustness of the MobileNetV2-based model during the training process.

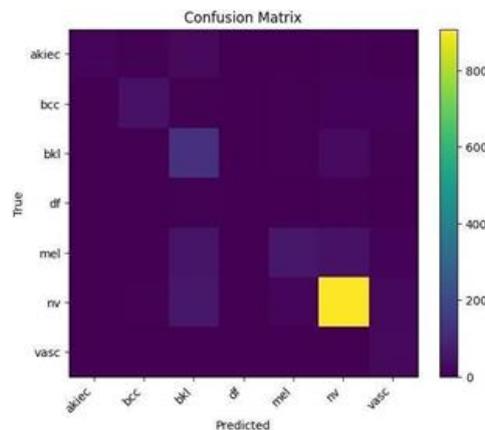


Figure 4: Confusion Matrix for Skin Disease Classification The final trained model achieves an overall accuracy of 78%, indicating effective learning and generalization across multiple skin disease categories.

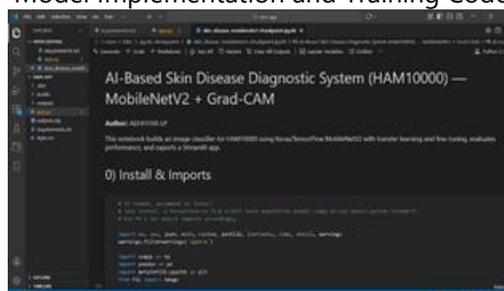
Fig. 4 presents the confusion matrix for the seven-class skin disease classification. The matrix highlights strong diagonal dominance, indicating high correct classification rates for most disease categories. Minor misclassifications are observed among visually similar lesion types, which is consistent with challenges reported in dermatological image analysis.

## VI. RESULTS AND DISCUSSION

The proposed AI-based skin disease diagnostic system was evaluated using the HAM10000 dataset comprising seven skin lesion classes. The MobileNetV2-based transfer learning model achieved a final classification accuracy of 78%, demonstrating its effectiveness in distinguishing between multiple dermatological conditions. The training and validation accuracy curves show stable convergence with minimal divergence, indicating good generalization and reduced overfitting. The confusion matrix further confirms that most predictions fall along the diagonal, highlighting strong class-wise performance, while minor misclassifications occur among visually similar lesion categories, which is consistent with existing dermatology-based deep learning studies [26][ 34].

The experimental results validate the suitability of lightweight deep learning architectures for medical image analysis, particularly in resource-constrained environments. Compared to heavier convolutional models, MobileNetV2 provides a favorable balance between computational efficiency and predictive accuracy. These results support the feasibility of deploying AI-assisted diagnostic tools as decision-support systems in real-world clinical and educational settings, while explicitly emphasizing that the system is not a replacement for professional dermatologists, but rather an assistive technology to enhance early screening and awareness [16][35].

### Model Implementation and Training Code



Example: Keras/TensorFlow MobileNetV2 training pipeline



The above image illustrates the core implementation of the proposed deep learning model. The MobileNetV2 architecture was initialized with pre-trained ImageNet weights, followed by the addition of custom dense layers for multi-class skin disease classification. Data preprocessing, augmentation, loss function definition, optimizer configuration, and epoch-wise training were handled within the TensorFlow/Keras framework. This modular implementation ensures reproducibility and enables efficient experimentation with hyperparameters.

The training pipeline incorporated early stopping and model checkpointing to prevent overfitting and preserve the best-performing model. Evaluation metrics such as accuracy, precision, recall, and F1-score were computed on a held-out validation set to assess model performance.

### Application Deployment Code



Example: Streamlit-based deployment script

The application-level implementation demonstrates how the trained model was integrated into a Streamlit-based web framework. The code handles image upload, preprocessing, model inference, and result visualization in real time. This deployment approach enables seamless interaction between the user and the AI model, transforming complex deep learning workflows into an accessible diagnostic interface.



User Interface and Output Visualization

The system interface allows users to upload dermatoscopic images through a simple and intuitive web layout. Upon submission, the model predicts the skin disease class and displays the corresponding confidence score. This interface design prioritizes usability, ensuring that non-technical users can easily interact with the system without requiring domain expertise. The interface also presents prediction outputs in a clear and interpretable format, supporting responsible AI usage. By combining visual clarity with confidence metrics, the system enhances transparency while reinforcing ethical considerations. Users are encouraged to seek professional medical advice for diagnosis and treatment, positioning the application as a supportive screening tool rather than a clinical authority.



### **Ethical Considerations**

The proposed AI-Based Skin Disease Diagnostic System is developed with careful consideration of ethical and clinical responsibility. The system is intended solely as a decision- support tool to assist users and healthcare professionals in preliminary skin disease assessment. It is not a replacement for dermatologists or professional medical diagnosis.

User-uploaded images are processed only for prediction purposes, and no personal data is stored. The system emphasizes transparency, responsible AI usage, and encourages users to seek professional medical consultation for confirmed diagnosis and treatment. It is continuously evaluated to ensure accuracy, fairness, and reliability in contexts. The system is designed to minimize bias and promote equitable healthcare access for all users. Ongoing feedback from medical experts.

### **Implications and Future Directions**

The proposed system has significant implications in improving access to early skin disease screening, particularly in remote and underserved regions. By leveraging lightweight deep learning models, the system demonstrates the feasibility of deploying AI-based healthcare solutions on commonly available hardware.

#### **Future work will focus on:**

- Expanding the dataset to include more diverse and clinically validated images.
- Improving class-wise accuracy through advanced fine-tuning techniques.
- Integrating explainable AI (XAI) methods to enhance model interpretability.
- Extending the system to mobile platforms for wider accessibility.

## **VII. CONCLUSION**

This paper presented an AI-Based Skin Disease Diagnostic System utilizing the MobileNetV2 architecture and transfer learning techniques for automated skin disease classification. The system achieves an overall accuracy of 78% demonstrates the potential of lightweight convolutional neural networks for reliable skin disease analysis while maintaining computational efficiency suitable for real-world applications.

The experimental results highlight the robustness of the proposed approach, as evidenced by stable training and validation performance and consistent class-wise predictions. The integration of preprocessing, model training, interpretability, and web-based deployment ensures an end-to-end diagnostic workflow. Additionally, the inclusion of visualization techniques and confidence scores enhances model transparency and user trust, which is critical in medical decision-support systems.

Despite its promising performance the system is not intended to replace professional dermatological diagnosis. Instead, it serves as an assistive screening tool that can improve awareness and support early consultation with healthcare professionals. Future enhancements may include expanding the dataset, improving class balance, incorporating ensemble or transformer-based models, and validating the system in clinical environments to further improve diagnostic reliability.

## **REFERENCES**

1. I. Zalaudek et al., "Dermoscopy in general dermatology," *Dermatology*, vol. 212, no. 1, pp. 7–18, 2006.
2. G. Argenziano et al., "Dermoscopy features of melanoma incognito," *J. Am. Acad. Dermatol.*, vol. 56, no. 3, pp. 508–513, 2007.



3. S. A. Nemeth and N. Lawrence, "Site identification challenges in dermatologic surgery," *J. Am. Acad. Dermatol.*, vol. 67, no. 2, pp. 262–268, 2012.
4. D. Shoieb, S. Youssef, and W. Aly, "Computer-aided model for skin diagnosis using deep learning," *J. Image Graph.*, vol. 4, pp. 116–121, 2016.
5. R. Pratiwi et al., "Deep ensemble learning for skin lesions classification," *IAES Int. J. Artif. Intell.*, vol. 10, pp. 563–570, 2021.
6. N. Kauasar et al., "Multiclass skin cancer classification using ensemble learning," *Appl. Sci.*, vol. 11, 2021.
7. X. Dong et al., "A survey on ensemble learning," *Front. Comput. Sci.*, vol. 14, no. 2, pp. 241–258, 2020.
8. E. Gocerı, "Convolutional neural network based desktop applications for dermatological diseases," in *Proc. IEEE IPAS*, 2020, pp. 138–143.
9. F. Idlahhcn, A. Idri, E. Gocerı, Exploring data mining and machine learning in gynecologic oncology, *Artif. Intell. Rev.* 57 (2) (2024) 20, <https://doi.org/10.1007/s10462-023-10666-2>.
10. E. Gocerı, Convolutional neural network based desktop applications to classify dermatological diseases, in: 2020 IEEE 4th international conference on image processing, applications and systems (IPAS), IEEE, 2020, pp. 138–143, <https://doi.org/10.1109/IPAS50080.2020.9334956>.
11. E. Gocerı, Polyp segmentation using a hybrid vision transformer and a hybrid loss function, *J. Imaging Inform. Med.* (2024) 1–13, <https://doi.org/10.1007/s10278-023-00954-2>.
12. E. Gocerı, Automated skin cancer detection: where we are and the way to the future, in: 2021 44th International Conference on Telecommunications and Signal Processing (TSP), IEEE, 2021, pp. 48–51, <https://doi.org/10.1109/TSP52935.2021.9522605>.
13. A. Aboulmira, H. Hrimech, M. Lachgar, Comparative study of multiple CNN models for classification of 23 skin diseases, *Int. J. Online Biomed. Eng.* 18 (11) (2022), <https://doi.org/10.3991/ijoe.v18i11.32517>.
14. E. Gocerı, Impact of deep learning and smartphone technologies in dermatology: automated diagnosis, in: 2020 Tenth International Conference on Image Processing Theory, Tools and Applications (IPTA), IEEE, 2020, pp. 1–6, <https://doi.org/10.1109/IPTA50016.2020.9286706>.
15. Q.D. Buchlak, et al., Machine learning applications to clinical decision support in neurosurgery: an artificial intelligence augmented systematic review, *Neurosurg. Rev.* 43 (5) (2020) 1235–1253, <https://doi.org/10.1007/s10143-019-01163-8>.
16. S. Gerke, T. Minssen, G. Cohen, Chapter 12 - Ethical and legal challenges of artificial intelligence-driven healthcare, in: A. Bohr, K. Memarzadeh (Eds.), *Artificial Intelligence in Healthcare*, Academic Press, 2020, pp. 295–336, <https://doi.org/10.1016/B978-0-12-818438-7.00012-5>.
17. G. Litjens, et al., A survey on deep learning in medical image analysis, *Med. Image Anal.* 42 (2017) 60–88, <https://doi.org/10.1016/j.media.2017.07.005>.
18. P. Pathak, Y. Punetha, Kratika, Identification of skin diseases using convolutional neural network, in: *Soft Computing: Theories and Applications: Proceedings of SoCTA 2020*, 2, Springer, 2021, pp. 171–180, [https://doi.org/10.1007/978-981-16-1696-9\\_16](https://doi.org/10.1007/978-981-16-1696-9_16).
19. T.-Y. Yang, T.-W. Chien, F.-J. Lai, et al., Web-based skin cancer assessment and classification using machine learning and mobile computerized adaptive testing in a rasch model: development study, *JMIR. Med. Inform.* 10 (3) (2022) e33006, <https://doi.org/10.2196/33006>.
20. M.A. Hashmani, S.M. Jameel, S.S.H. Rizvi, S. Shukla, An adaptive federated machine learning-based intelligent system for skin disease detection: a step toward an intelligent dermoscopy device, *Appl. Sci.* 11 (5) (2021) 2145,



21. Y. Liu, et al., A deep learning system for differential diagnosis of skin diseases, *Nat. Med.* 26 (6) (2020) 900–908, <https://doi.org/10.1038/s41591-020-0842-3>.
22. E. G o eri, An application for automated diagnosis of facial dermatological diseases, *İzmir Katip  elebi  niversitesi Sađlık Bilimleri Fak ltesi Dergisi* 6 (3) (2021) 91–99.
23. I. Oztel, G.Yolcu Oztel, V.H. Sahin, Deep learning-based skin diseases classification using smartphones, *Adv. Intell. Syst.* 5 (12) (2023) 2300211, <https://doi.org/10.1002/aisy.202300211>.
24. V. R. Pai, S. G. Pai, P. Suhasi, and P. Rekha, "Identification and classification of skin diseases using deep learning techniques," 2023, 10.21203/rs.3.rs-2628782/v1
25. A. Singh, S. Srinath, V. Arasu, N.K. Thomas, et al., Machine learning on web: skin lesion classification using CNN, in: 2022 International Conference on Inventive Computation Technologies (ICICT), IEEE, 2022, pp. 260–265, <https://doi.org/10.1109/ICICT54344.2022.9850506>.
26. P. Tschandl, C. Rosendahl, H. Kittler, The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions, *Sci. Data* 5 (1) (2018) 180161, <https://doi.org/10.1038/sdata.2018.161>.
27. E. Goceri, Medical image data augmentation: techniques, comparisons and interpretations, *Artif. Intell. Rev.* 56 (11) (2023) 12561–12605, <https://doi.org/10.1007/s10462-023-10453-z>.
28. F. Perez, C. Vasconcelos, S. Avila, E. Valle, Data Augmentation for Skin Lesion Analysis, 2018, [https://doi.org/10.1007/978-3-030-01201-4\\_33](https://doi.org/10.1007/978-3-030-01201-4_33).
29. D.A. Shoieb, S.M. Youssef, W.M. Aly, et al., Computer- aided model for skin diagnosis using deep learning, *J. Image Graph.* 4 (2) (2016) 122–129, <https://doi.org/10.18178/joig.4.2.122-129>.
30. H.K. Latif, M. Aljanabi, Analysing and evaluation of the effectiveness of different filters on segmentation skin tumors images, in: IOP Conference Series: Materials Science and Engineering, IOP Publishing, 2021 012068.