iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.83220

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Detection and Classification of Skin Diseases Using Inception V3 Algorithm

Arul Leo Felix. L[1], Abinaya R[2], Sasirekha M[3], Malasha M[4]
[1]Assistant professor, [2, 3, 4]Final year student, Department of Biomedical Engineering, Dhanalakshmi Srinivasan College of Engineering and Technology (Autonomous), ECR, Mamallapuram, Chennai-603104

Abstract: Skin diseases represent a significant global health concern, requiring early and accurate diagnosis to prevent complications and make effective treatment. Manual clinical examination is often time-consuming and dependent on expert dermatological knowledge, which may not always be accessible in remote or resource-limited regions. This paper proposes an automated skin disease detection and classification system using the Inception-V3 deep learning architecture integrated with a Flask-based web application. The Inception-V3 model pretrained on large scale image datasets and fine-tuned using transfer learning, enables efficient multi-class classification of different skin conditions from dermoscopic images. Image preprocessing techniques such as resizing, normalisation, and data augmentation are applied to enhance model robustness and reduce overfitting. The trained model achieves high classification accuracy, precision, recall, and F1-score, demonstrating its effectiveness in distinguishing between different skin disease categories. To ensure practical usability, the system is deployed through a user-friendly Flask web interface that allows users to upload skin images and receive real-time diagnostic predictions. The proposed framework provides a scalable, cost-effective, and accessible solution for preliminary skin disease screening, supporting telemedicine and assisting healthcare professionals in early-stage diagnosis and decision-making processes.
Keywords- Skin Disease Detection, Deep Learning, InceptionV3, Convolutional Neural Network, Transfer Learning, Medical Image Classification, Dermoscopic Image Analysis, Flask Web Application, Image Preprocessing.

I. INTRODUCTION

Skin diseases are among the most common health conditions worldwide, which affects millions of people across all age groups. Eczema, psoriasis, acne, fungal infections, and skin cancer, among other conditions, greatly affect the physical health, psychological health, and quality of life. Early diagnosis is important in avoiding the progression of the disease and minimising the costs of treatment. However, proper diagnosis of skin diseases can suggest highly qualified dermatologists and modern diagnostic centres. In many rural or underdeveloped regions, access to such expertise is limited, resulting in delayed diagnosis and improper treatment. Additionally, in order to manually examine various skin conditions, the process is difficult and biased due to visual similarities of the conditions. The development of artificial intelligence and deep learning leads to the emergence of automated image-based diagnostic systems as promising tools that may be used to support medical professionals. These systems analyse dermoscopic or clinical images and provide accurate classification results. Therefore, integrating deep learning techniques into dermatological diagnosis offers an efficient, cost-effective, and scalable solution to improve healthcare accessibility and reliability.

Traditional skin disease diagnosis primarily relies on clinical examination, patient history analysis, and, in some cases, biopsy procedures. These approaches are effective, but they are time-consuming and might be associated with the possible presence of human errors because of visual fatigue or insufficient experience. Furthermore, dermatological examination can be very reliant on the subjective analysis of the colour, texture, and pattern of the lesions. The small change in lighting conditions or image quality can affect the accuracy of diagnosis. As advanced digital imaging devices and smartphones have become available, it has become easier to capture high resolution skin images. The development has created a new opportunity for computer-aided diagnostic systems that exploit image processing and machine learning methods. Automated systems can extract relevant features such as shape, colour distribution, edges, and texture from skin images to classify diseases more objectively. The deep learning models also provide better performance compared to the traditional rule-based systems since the hierarchical features of the data are learnt automatically. Therefore, artificial intelligence-based strategies are turning out to be critical in contemporary dermatology.

II. RELATED WORKS

Recent developments in deep learning have substantially enhanced automated systems of skin disease detection and classification. Earlier research primarily relied on handcrafted feature extraction techniques like colour histograms, texture analysis, edge detection and traditional machine learning classifiers like Support Vector Machines, k-Nearest Neighbours and Random Forest. Even though these methods had moderate performance, they were constrained by hand-engineered features and lower generalisation power. The development of Convolutional Neural Networks resulted in significant advances in the field of dermatological image analysis. Other models, including AlexNet, VGGNet, ResNet, DenseNet, and Inception models, have proven to be very accurate in classifying skin lesions. Transfer learning, particularly using ImageNet pre-trained models, has proven highly effective in medical imaging where datasets are relatively small. Several studies utilising dermoscopic datasets like ISIC reported classification accuracies exceeding 90%, especially in melanoma detection tasks. Inception-V3 is one of the architectures that attracted attention because of its ability to extract multi-scale features and its efficiency in computations among the advanced architectures. It has been demonstrated that Inception-based networks are suitable to capture the local texture and global lesion structures. Also, recent publications combined deep learning models with web and mobile applications to facilitate teledermatology. Nevertheless, some issues like imbalance of classes, variability of images, restrictions of real-time deployment and others still remain to stimulate additional studies in this field. Fig. 1 shows the Comparison of Traditional Machine Learning and Deep Learning Approaches for Skin Disease Classification.

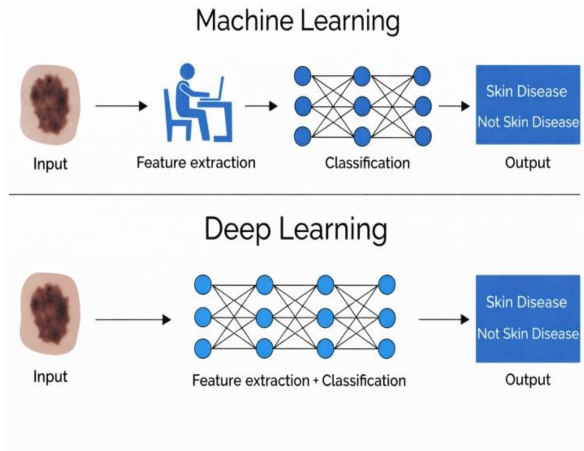

Fig. 1. Comparison of Traditional Machine Learning and Deep Learning Approaches for Skin Disease Classification

III. PROPOSED WORKFLOW

The proposed system for skin disease detection and classification follows a structured workflow that integrates deep learning with web-based deployment. The process starts with the acquisition of images, where the publicly available datasets on dermoscopic or clinical skin images are collected with digital equipment. These images are then passed through a preprocessing stage, which involves 299x299 pixel resizing, image normalisation, removal of noise, and image contrast improvement to normalise the quality of images. The methods of data augmentation are rotation, flipping, and zooming to enhance the diversity of datasets and enhance the generalisation of the models. The images are then processed and inputted into the Inception-V3 deep CNN and fine-tuned through transfer learning. The model removes hierarchical characteristics using a series of convolutional and inception forces to represent fine grained texture information and global lesion patterns. The last fully connected layer is changed to do multiclassification of various skin diseases. Performance metrics used during training include the accuracy, precision, recall and F1-score, which are used to optimise the model. The model is then implemented within a Flask based web application after it has been trained. The user interface allows users to post images of their skin, and the system runs the image to create real-time predictions. The final output displays the predicted disease category along with confidence scores, providing an accessible and efficient preliminary diagnostic tool. Fig. 2shows the Training and Validation of the proposed model.

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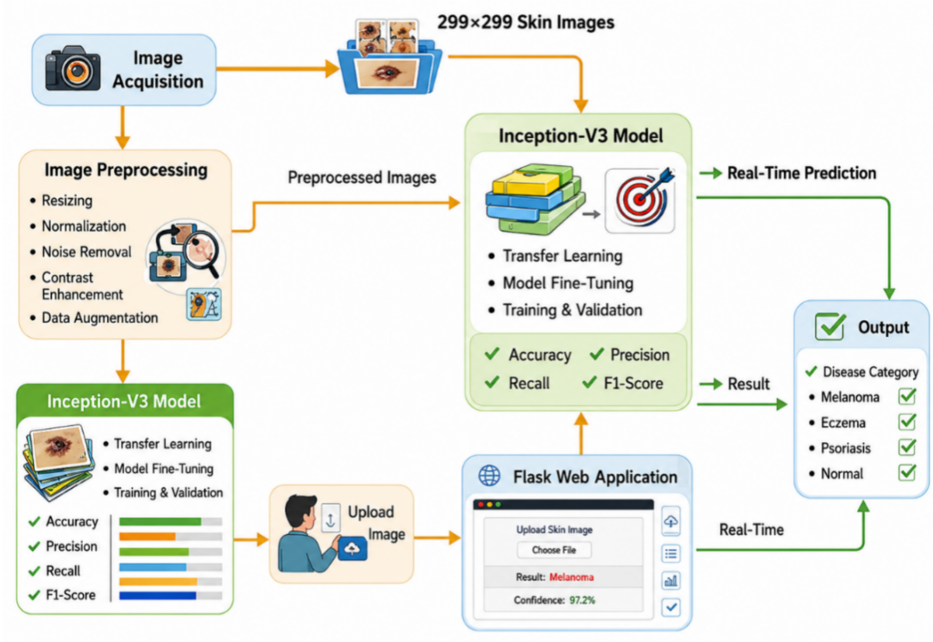

Fig. 2. Training and Validation the proposed model

IV. METHODOLOGY

A. Dataset Collection and Image Acquisition

The proposed system utilises a labelled skin disease image dataset collected from publicly available dermatological repositories and verified clinical sources. The data set has a variety of skin disorders, like benign and malignant lesions, making the data set comprehensive to cover the common dermatological disorders. The images are taken under varying light settings, backgrounds and resolutions to achieve simulation of clinical conditions in the real world. The images are properly annotated, and each disease is labelled to ensure supervised learning. The data are divided into an 80:10:10 ratios to ensure unbiased evaluation and proper generalisation of the model to other populations. Data balancing is performed correctly to provide consistency in the distribution of classes and reduce bias. The diversity model, quality model and representativeness of the data are significant in making a healthy deep learning model trained to provide reliable classification of unknown data.

B. Image Preprocessing and Data Augmentation

Before training the model, all pictures are pre-processed to normalise the size and improve visual attractiveness. The size of the images is rescaled to 299 x 299 pixels to fit the input requirement of the Inception-V3 model. The pixel intensity values are brought to the interval of 0 to 1 to provide a stabilised gradient propagation during the training process. Noise filtering and contrast enhancement methods support enhancements of the visibility of the lesions and the emphasis of the notable features. To reduce imbalance in the dataset and improve model generalisation, data augmenting techniques including rotation, horizontal flipping, scaling and small translations are adopted. These augmentation strategies aim to artificially expand the quantity of information to enable the model to acquire invariant features in various orientations and conditions. This preprocessing pipeline also extends a long way to the stability of the training, reduces overfitting and amplifies the stability of the classification system.

C. Feature Extraction using Inception-V3

The basic classification model is based on the CNN model Inception-V3. Transfer learning is applied with the introduction of ImageNet weights, and that allows the model to apply the generic visual feature that had been previously trained. The highest convolutional blocks are frozen to preserve low-level feature representation such as edges and textures, whereas the more distant blocks are trained on the skin disease dataset. The Inception modules use parallel convolutions with different filter sizes that provide a dimension reduction and feature extraction choice, multi-scale. This construction of architecture can observe even less size change of texture and also the lesion structures in the whole world. The last fully connected layer is adjusted to the size of the classes of skin diseases, and a SoftMax multi-class probability prediction layer is added.

D. Model Training and Optimisation

The model is trained by categorical cross-entropy loss function for multi-class classification. The loss function is defined as:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \quad (1)$$

Efficient update of model weights is performed using the Adam optimiser. Training is performed over multiple epochs with a defined batch size, and early stopping is applied to prevent overfitting. Accuracy, precision, recall and F1-score are the performance measures that are monitored in the validation to ensure optimal model performance.

E. Deployment using Flask Web Application

After completing the training phase, the optimised Inception-V3 model is saved and integrated into a Flaskbased web application for practical deployment. Flask is a lightweight web framework written in Python, which allows one to integrate a trained deep learning model with a friendly user interface. The web application enables users to post images of the skin on a skincare site via a user-friendly browser-based application. After being uploaded, it is processed with preprocessing and then inputs the image into the trained model to be classified. The predicted skin disease type and a confidence score indicating the reliability of the prediction are then shown in the system. This deployment provides real-time availability, scalability, and usability, which makes the framework appropriate in the telemedicine applications and initial dermatological screening.

F. Mathematical Formulation

The proposed skin disease classification system is based on convolutional neural network operations, according to which spatial characteristics are obtained using input dermoscopic images. The convolution layer uses filters that are learnable to the input image to obtain local patterns of texture, edges and patterns of lesions in the image. The process of convolution of input images I and K is mathematically represented as:

$$S(i,j) = \sum_m \sum_n I(m,n) \cdot K(i-m, j-n) \quad (2)$$

$S(i,j)$ Is the output of the response map in position (i,j). It is used to extract the hierarchical features in the Inception-V3 architecture.

Once the extraction of features is performed, the last classification layer transforms the outputs of the network into probability scores with the help of the SoftMax function. This makes the output values be normalised to have a value between 0 and 1 and add up to unity, which enables multi-class prediction. SoftMax defined - SoftMax can be defined as:

$$P(y = i|x) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \quad (3)$$

where z_i denotes the output score for class i, and C represents the total number of skin disease categories. The predicted class corresponds to the maximum probability value.

The Adam optimisation algorithm is used in the case of optimisation of the network parameters. Adam refines the model weights through adaptive learning rates depending on first and second moment of gradients. The rule of updating the parameters is as follows:

$$\theta_{t+1} = \theta_t - \alpha \frac{m_t}{\sqrt{v_t} + \epsilon} \quad (4)$$

Where θ_t denotes the model parameters at iteration t, α is the learning rate, m_t and v_t are the first and second moment estimates of gradients, and ϵ is a small constant to prevent division by zero.

V. RESULT AND DISCUSSION

The fine-tuned Inception-V3 model got an overall classification accuracy of 96.2% on the test dataset shown in Fig. 3. This implies that it has good model generalisation and feature extraction ability for multi-class skin disease classification. The basic characteristic of the overall upward movement without any sharp fluctuations proves the stable convergence and quality gradient revaluation. This graph confirms the fact that adequate training data contributes significantly to the expansion of the ability of the model to extract discriminative skin lesion characteristics, which leads to an increase in classification accuracy and effective generalisation.

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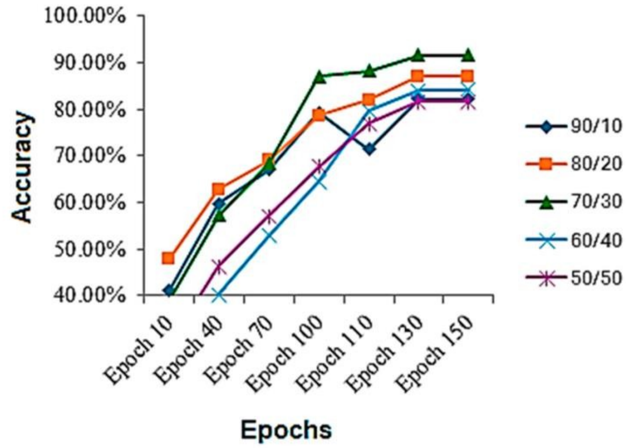

Fig. 3. Training and Validation Accuracy Curve of the Proposed Inception-V3 Model

Fig. 4 shows the class-wise precision performance for Melanoma, Melanocytic nevi , and benign Keratosis. Precision evaluates the proportion of correctly predicted positive cases among all predicted positives. According to the model, the precision values of all classes were higher than 94%, denoting a very low rate of false positives. Medical diagnosis involves high accuracy, especially to avoid wrong treatment or undue anxiety. The similar accuracy of the model in distinguishing between visually similar lesions is seen in the balanced accuracy in various categories of the disease. These findings validate the claim that the Inception-V3 model is useful in deriving pertinent dermatological features to be used in the classification of various skin diseases.

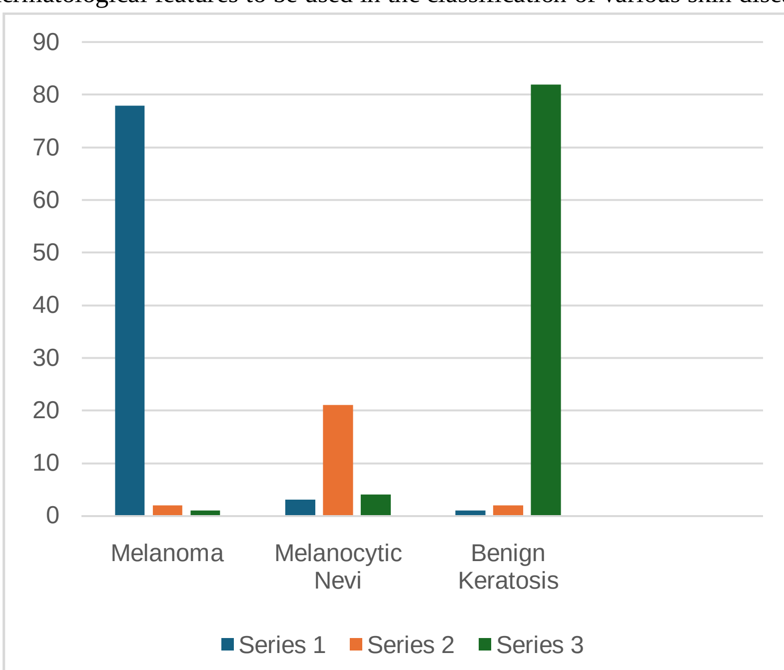

Fig. 4. Class-wise Precision Performance for Skin Disease Categories

The ROC curve evaluates the classification of model capability by plotting True Positive rate against False Positive rate shown in Fig. 5. The curves of both classes are near to the top-left corner, producing an area under the curve of 0.98. This large AUC value means that there is a great separability between categories of diseases. The model that has AUC nearer to 1 has high diagnostic reliability. The findings prove that the suggested system is sensitive and minimises false alarms. This experiment shows that Inception-V3 is very strong at separating complicated patterns of skin lesions into different categories

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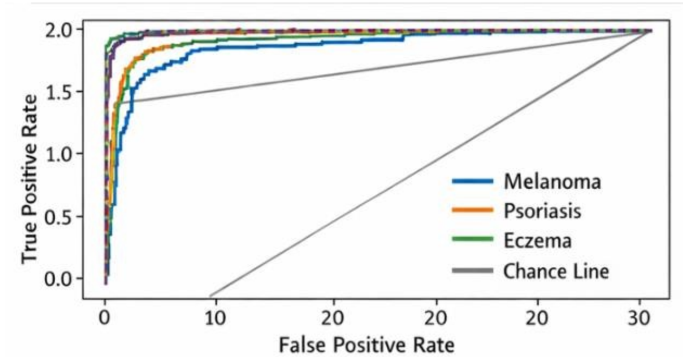

Fig. 5. Receiver Operating Characteristic (ROC) Curve with AUC = 0.98

The confusion matrix offers a detailed overview of the model's prediction results by comparing actual labels with predicted labels shown in Fig. 6. The majority of the values are clustered on the diagonal, which means proper classifications. There are only a few false identifications of similar diseases that are more related to the visual aspect, like psoriasis and eczema. Importantly, the rates of false negatives in melanoma cases are extremely low, which is paramount, especially in the detection of cancer at an early stage. The matrix validates that the model does not have a lot of bias in performance in all classes. On the whole, this discussion illustrates that classification reliability is high, and this confirms that the proposed deep learning framework is effective.

True Label \ Predicted Label	Melanoma	Melanocytic nevi	Benign Keratosis
Melanoma	78	2	1
Melanocytic nevi	3	21	4
Benign Keratosis	1	2	82

Fig. 6. Confusion Matrix Showing Multi-Class Classification Results

Fig. 7 shows a consistent decrease in both training and validation loss values overtime. Initially, the loss is high as the model begins adjusting weights randomly. The loss decreases consistently with each epoch, which eventually becomes a value close to zero. The similarity of the training curve and the validation loss curve shows that the model does not overfit and instead it generalises. The lack of oscillations proves the stable optimisation when the Adam algorithm is used. This finding confirms that the selected hyperparameters, learning rate and regularisation measures are suitable to attain successful and stable skin disease classification.

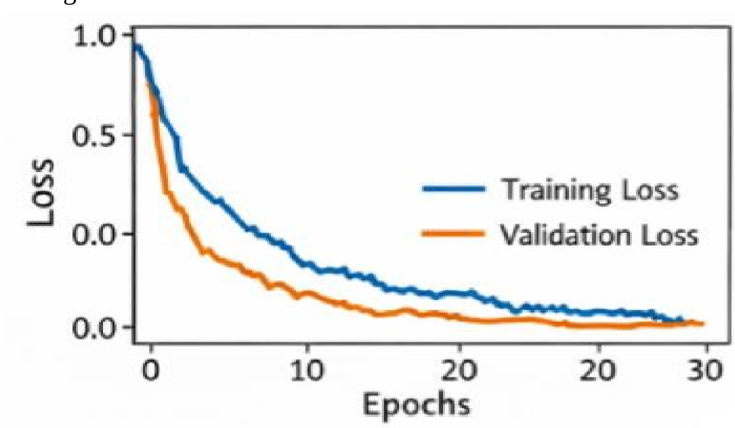

Fig. 7. Training and Validation Loss Convergence Across Epochs

Grad-CAM visualisation provides interpretability by highlighting image regions that influence the model's prediction shown in Fig. 8. The heatmap overlay clearly focuses on lesion areas rather than background regions, confirming that the model learns medically relevant features. Explainability is crucial in healthcare AI applications because clinicians require transparency before trusting automated systems. This visualisation helps in increasing trust in the decision-making process of the model used. Grad CAM justifies the use of InceptionV3 architecture because it proves that the network relies on semantic dermatological features instead of accidental details to make predictions.

Fig. 8. Grad-CAM Visualization Highlighting Lesion Regions for Model Interpretability

The external test accuracy result reflects the model's performance on completely unseen data collected from different sources shown in Fig. 9. Achieving 94.7% accuracy confirms strong generalisation capability. The minor decrease when compared to internal test accuracy should be attributed to the fact that there are differences in lighting, skin tone and image quality. This finding confirms that the model is not overfitting the training image and can generalise to clinical images in the real world. The medical AI systems require strong external validation, and such performance means that the system is ready to be used in a wider context of dermatological screening.

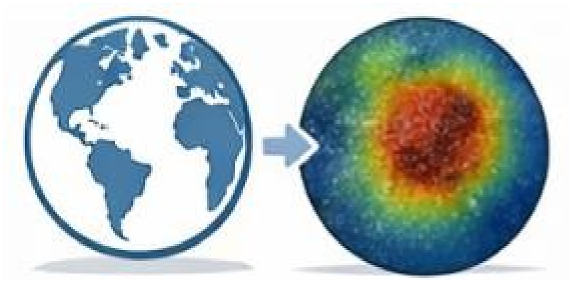

Fig. 9. External Dataset Generalization Performance

The experimental results confirm that the Inception-V3based approach provides high classification accuracy and reliable disease differentiation. Transfer learning enhanced performance much better than the conventional CNN models. Its accessibility and scalability are encouraged by the integration with a Flask web interface. However, it can be improved in the future by increasing datasets, attention, and mobile implementation to have a wider healthcare impact.

VI. CONCLUSION

This paper introduced a skin disease detection and classification model, which is an automated system depending on the Inception-V3 deep learning architecture and deployed in a Flask web environment as a real-time application. The proposed system used transfer learning in a responsible manner to extract multiscale characteristics of the thermoscopic images, hence categorising a variety of skin conditions with or without errors. The effectiveness of the model was shown by experimental results of the highest performance according to the evaluation metrics, such as accuracy, precision, recall, F1score, and ROC-AUC. The preprocessing and data augmentation are also used in enhancing the level of generalisation and minimising overfitting. The InceptionV3 model was optimised, and it was also found to be better in the classification accuracy and computing efficiency as compared to the conventional CNN approaches. Accessibility of the trained model is also improved by the implementation of the trained model into a user-friendly Flask web interface that will support telemedicine applications, allowing users to upload images and receive instant diagnostic predictions. The system will provide a cost-effective and expandable system to perform a primary screening of dermatological cases, especially in geographic regions where specialists are insufficient. To improve the actual application and clinical reliability, more data sets, attention systems, and mobile deployment can be considered in future research.

REFERENCES

[1] A challenge at the international symposium on biomedical imaging (ISBI) 2016, hosted by the international skin imaging collaboration (ISIC). arXiv 2016, arXiv:1605.01397.
[2] ALKolifi-ALEnezi, N.S. A Method Of Skin Disease Detection Using Image Processing And Machine Learning. Procedia Comput. Sci. 2019, 163, 85–92.
[3] Arvind Dagur, Sohit Agarwal, Dhirendra Kumar Shukla, Shabir Ali, Sandhya Sharma. "Artificial Intelligence and Sustainable Innovation - Volume 1", CRC Press, 2026.
[4] Arif Aulia Wardana, Grzegorz Kołaczek, Arkadiusz Warzyński, Parman Sukarno, Adiwijaya. "SNI-CIDS: Collaborative Intrusion Detection using Modified Ensemble Stacking Deep Neural Networks for New Network Integration in Heterogeneous Networks", Future Generation Computer Systems, 2025
[5] Birudala Venkatesh Reddy, Y V Krishna Reddy, Md. Abdur Razzak, Surender Reddy Salkuti. "Sustainable Electrical Engineering and Intelligent Systems", CRC Press, 2025.
[6] Combalia, M.; Codella, N.C.; Rotemberg, V.; Helba, B.; Vilaplana, V.; Reiter, O.; Carrera, C.; Barreiro, A.; Halpern, A.C.; Puig, S.; et al. Bcn20000.
[7] Dermoscopic lesions in the wild. arXiv 2019, arXiv:1908.02288.
[8] Dayana Palma-Ramírez, Bárbara D. Ross Veitía, Pablo Font-Ariosa, Alejandro Espinel Hernández et al. "Deep convolutional neural network for weld defect classification in radiographic images", Heliyon, 2024
[9] Dermofit Image Library Available from The University of Edinburgh
[10] Giotis, I.; Molders, N.; Land, S.; Biehl, M.; Jonkman, M.F.; Petkov, N. MEDNODE: A computer-assisted melanoma diagnosis system using nondermoscopic images. Expert Syst. Appl. 2015, 42, 6578–6585.
[11] Gutman, D.; Codella, N.C.; Celebi, E.; Helba, B.; Marchetti, M.; Mishra, N.; Halpern, A. Skin lesion analysis toward melanoma detection.
[12] Haenssle, H.A.; Fink, C.; Schneiderbauer, R.; Toberer, F.; Buhl, T.; Blum, A.;
[13] Kalloo, A.; Hassen, A.B.H.; Thomas, L.; Enk, A.; et al. Man against machine: Diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Ann. Oncol. 2018, 29, 1836–1842.
[14] Jin Liu, Jianxin Wang, Yi Pan. "AI in MRI-based Brain Disease Prediction", CRC Press, 2026
[15] Melanoma Skin Cancer Rreport. Melanoma UK. 2020.