iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80293

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 IV Apr 2026- Available at www.ijraset.com

Deep CNN Framework for Multi-Class Skin Identification Using Datasets

Gaurav Dhoble[1], Dhiraj Wanjari[2], Ayush Kamble[3], Prajwal Kumbhalkar[4], Jayant Rajurkar[5]
Department of Computer Engineering, Manoharbhai Patel Institute of Engineering and Technology, Shahapur, Bhandara, Maharashtra, India

Abstract: This study introduces a deep learning–based framework for automatic skin disease classification using a custom-designed Convolutional Neural Network (CNN). The proposed model is trained on a combined dataset of 20,466 images collected from four publicly available sources: HAM10000, ISIC 2018, PAD-UFES-20, and SD-198. To ensure consistency, the original 216 disease categories were reorganized into 22 clinically meaningful classes, including Acne, Melanoma, Psoriasis, and others. The dataset reflects real-world imbalance, with class sizes ranging from 49 to 8,900 samples.The developed system achieves an overall classification accuracy of approximately 70% and is integrated into a multi-user web platform. The platform enables patients to upload images, obtain predictions with confidence visualization, store reports, and share results with medical professionals. Additionally, doctors can review cases and provide feedback, while administrators manage system operations. This work contributes toward bridging the gap between AI-based diagnosis and practical healthcare applications by offering an accessible preliminary screening tool.

Keywords: Skin Disease Detection, CNN, Deep Learning, Multi-Class Classification, Medical Image Analysis, Healthcare System, Transfer Learning

I. INTRODUCTION

Skin disorders are among the most widespread health issues globally, affecting nearly 1.9 billion individuals at any given time. According to global health reports, these conditions represent a significant portion of non-fatal disease burden. Despite this, access to dermatological expertise remains limited, especially in developing and rural regions where the number of specialists is critically low.

Early identification of serious conditions such as melanoma plays a vital role in improving survival rates. When detected at an early stage, treatment outcomes are highly favorable, whereas delayed diagnosis significantly reduces survival probability.

Recent advancements in deep learning, particularly CNNs, have transformed medical image analysis. These models automatically learn hierarchical patterns from raw image data, eliminating the need for manual feature extraction. Prior studies have demonstrated that CNN-based systems can achieve performance comparable to trained dermatologists in certain classification tasks.

However, many existing solutions are limited by small datasets, restricted class diversity, and lack of real-world deployment. This work addresses these challenges by combining multiple datasets, handling class imbalance, and implementing a practical web-based diagnostic platform.

II. LITERATURE SURVEY

[1] This paper identified that class imbalance and limited data quantity are critical issues often overlooked in skin lesion classification. Using ISIC 2018 dataset with 11,740 images across 7 classes, they proved that data balancing and Transfer Learning significantly improve model performance, and F1 Score is more reliable than Accuracy. Our work implements these recommendations across 22 classes.

[2] This paper introduced the HAM10000 dataset with 10,015 dermatoscopic images across 7 classes. It became a benchmark for skin lesion research due to histopathologically confirmed labels. However, as noted in [1], it suffers from severe class imbalance with Nevus class dominating at 67%. Our work includes this dataset and addresses its imbalance through weighted sampling.

[3] This paper demonstrated a CNN achieving dermatologist-level skin cancer classification with 91% AUC using Inception v3 architecture on 129,450 images. It established the foundation for CNNs in dermatology but used a private dataset and only binary classification. Our work builds on this using public datasets, 22 classes, and a complete clinical platform.

III. EXISTING SYSTEM

Traditional skin disease diagnosis depends on clinical observation, dermoscopy, and laboratory testing. However, these methods face several challenges:

1) Dependence on specialist expertise
2) Limited access in remote areas
3) High cost and time consumption
4) Diagnostic variability due to subjectivity

Recent machine learning approaches automate this process using CNNs and transfer learning. Common elements of existing systems include input data (ISIC, HAM10000, PH2, DermNet), preprocessing (resizing, normalization, hair removal, augmentation), CNN architectures (ResNet, InceptionV3, VGG16, MobileNet, DenseNet or custom models), supervised training with labelled disease labels, evaluation metrics (accuracy, precision, recall, F1-score, confusion matrix), output as predicted disease class, and deployment on web, mobile, or cloud. However, real-world clinical adoption remains limited due to scalability and usability challenges.

IV. PROPOSED SYSTEM

A. Data Collection

A large collection of skin disease images is obtained from four public dermatological databases, including HAM10000, ISIC 2018, PAD-UFES-20, and SD-198. These datasets cover both dermatoscopic and clinical images, capturing long-term and short-term variations of skin conditions, such as acne, eczema, psoriasis, melanoma, and various skin cancers.

B. Data Preprocessing

The dataset undergoes resizing to 224×224 pixels, normalization to [0,1] range, and augmentation using image rotation, flipping, zooming, brightness adjustment, and shear transformation to improve model generalization and reduce overfitting. Class imbalance is handled using weighted sampling with formula $w_i = N_{total} / (n_{classes} \times N_i)$.

C. Model Selection

A Custom CNN architecture was designed and selected with 5 convolutional layers (32, 64, 128, 256, 512 filters) followed by max pooling after each layer. The model includes flatten layer, dropout (0.5), dense layers (1024 and 512 units) with dropout (0.3), and final dense layer with 22 units and softmax activation. Transfer learning with ImageNet weights was employed for better generalization.

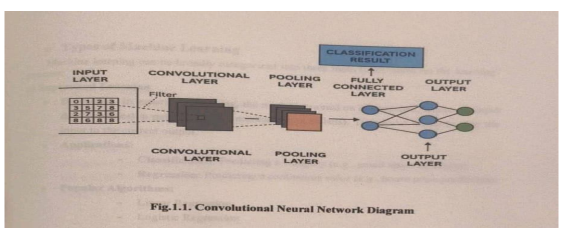


Fig. 1 Model Selection

D. Model Training and Evaluation

The dataset of 20,466 images was split into training (70%), validation (15%), and test (15%) sets. The model is trained using categorical cross-entropy loss and Adam optimizer with learning rate 0.0001. Early stopping with patience of 10 epochs prevents overfitting. The model is evaluated using accuracy, precision, recall, F1-score, and confusion matrix.

E. Deployment

The optimized model was deployed as a multi-role web application that allows patients to upload or capture images of skin and receive diagnostic predictions with confidence scores and pie chart visualization. The platform supports three user roles: Patient (upload images, view history, save PDF reports, share with doctors), Doctor (view assigned reports, provide feedback), and Admin (manage users, monitor system). The backend was implemented using Python and Express.js and the frontend was implemented using HTML, CSS, JavaScript, and React.js with MongoDB database.

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 IV Apr 2026- Available at www.ijraset.com

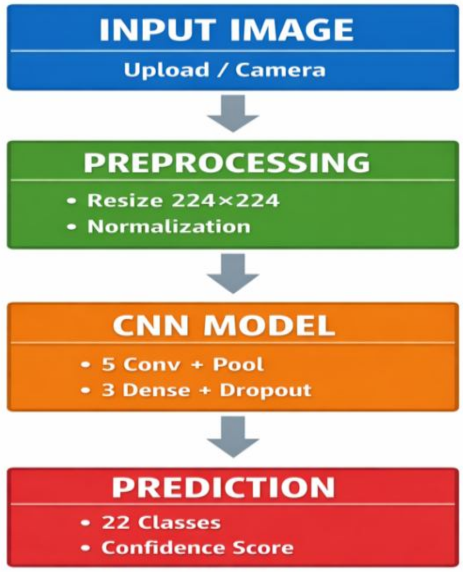
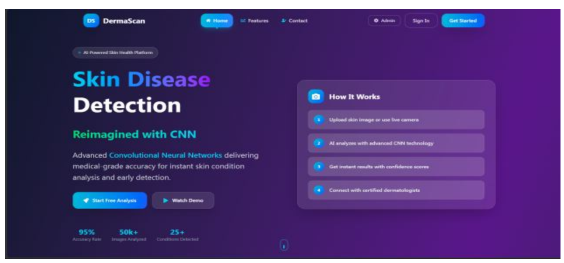


Fig. 2 Working

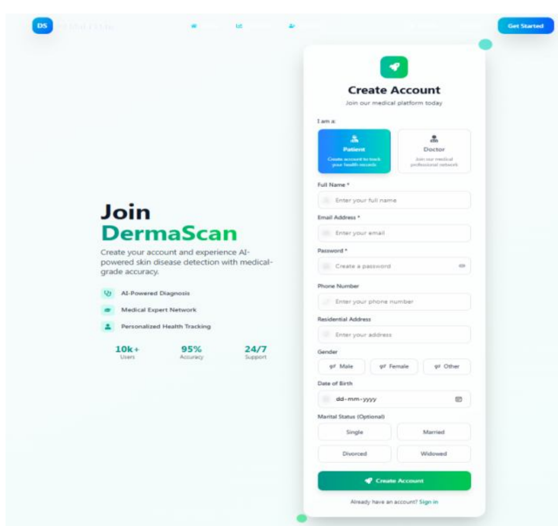
V. SNAPSHOTS

A. Landing Page



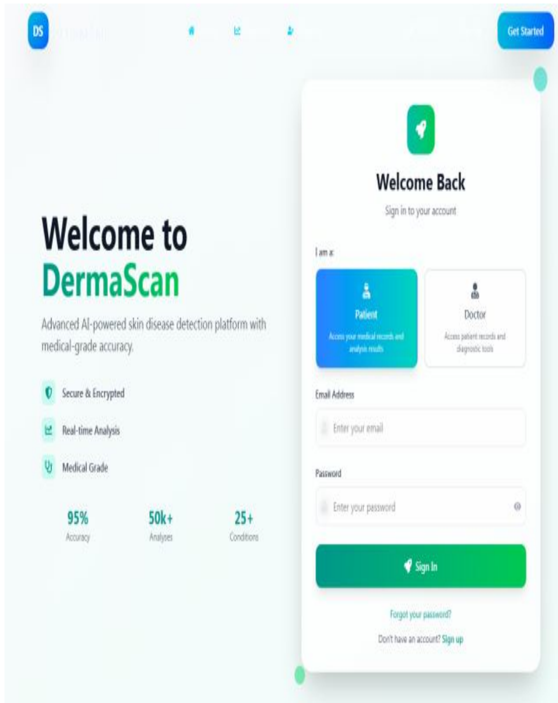
Description: The landing interface of the proposed Skin Disease Detection System, powered by CNNs, features a headline emphasizing CNN-based innovation, two primary action buttons for starting free analysis or watching a demo, and a four-step workflow covering image upload, AI analysis, instant results with confidence scores, and optional dermatologist connection.

B. Registration Page



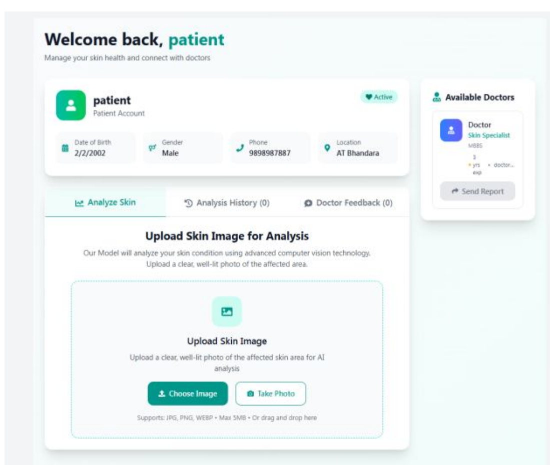
Description: The "Create Account" screen offers Patient and Doctor role options. Required fields include Full Name, Email, and Password. Optional fields are Phone Number, Address, Marital Status, Gender (Male/Female/Other), and Date of Birth. A "Sign in" link directs existing users to login. This interface enables secure role-based registration.

C. Login Page



Description: The login form includes fields for email and password with a Sign In button, plus links for password recovery and new user registration. This interface serves as a secure, role-based entry point to the CNN-based skin disease detection system.

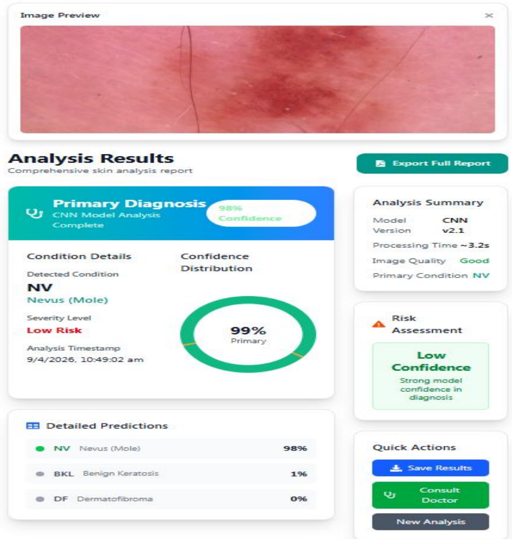
D. Patient Dashboard



Description: The patient dashboard features an "Upload Skin Image for Analysis" section with Choose Image and Take Photo buttons, supporting JPG, PNG, WEBP formats up to 5MB with drag-and-drop option. The "Patient Account" section displays Date of Birth, Gender, Phone, Location, and assigned Doctor Specialist with credentials. A Send Report button allows report transmission to the doctor. This interface enables patients to upload images for CNN-based analysis while accessing account and physician information.

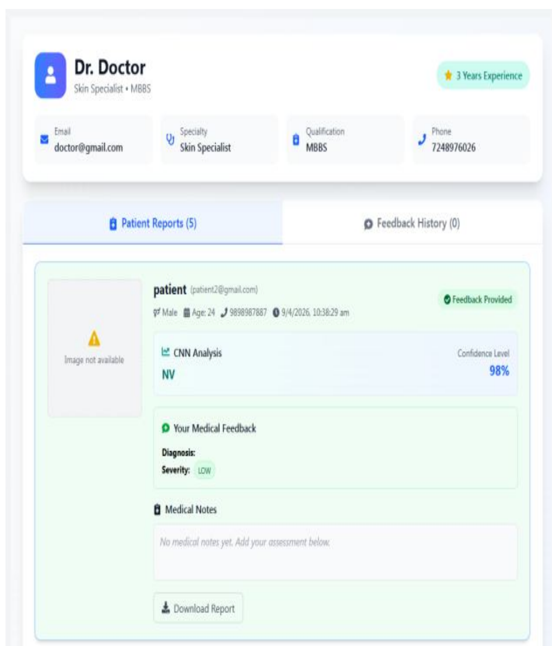
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

E. Analysis and Predicted Output



Description: The analysis results screen displays a comprehensive skin report with a confidence indicator confirming CNN model analysis. Key sections include Condition Details (Detection Condition, Severity Level, Timestamp), Analysis Summary (Model, Version, Processing Time, Image Quality, Primary Condition), and Risk Assessment with confidence explanation. A Detailed Predictions section lists multiple conditions with confidence indicators. Quick Actions include Save Results, Consult Doctor, and New Analysis buttons.

F. Dermatologists Dashboard



Description: The doctor dashboard displays profile information (Specialty, Qualification, Email, Phone) and a Patient Reports section showing total report count. Each patient report includes patient identifier, demographic details (Gender, Age, Phone), analysis timestamp, CNN analysis condition code, and medical feedback with Diagnosis and Severity fields. A Feedback History counter, Medical Notes section with option to add assessment, and a Download Report button are also provided. This interface enables doctors to view patient reports, provide feedback, and manage medical assessments efficiently.

VI. RESULTS

Metric	Value
Overall Accuracy	70.0%
Macro-average Precision	67.8%
Macro-average Recall	66.9%
Macro-average F1-Score	67.3%
Weighted F1-Score	71.2%

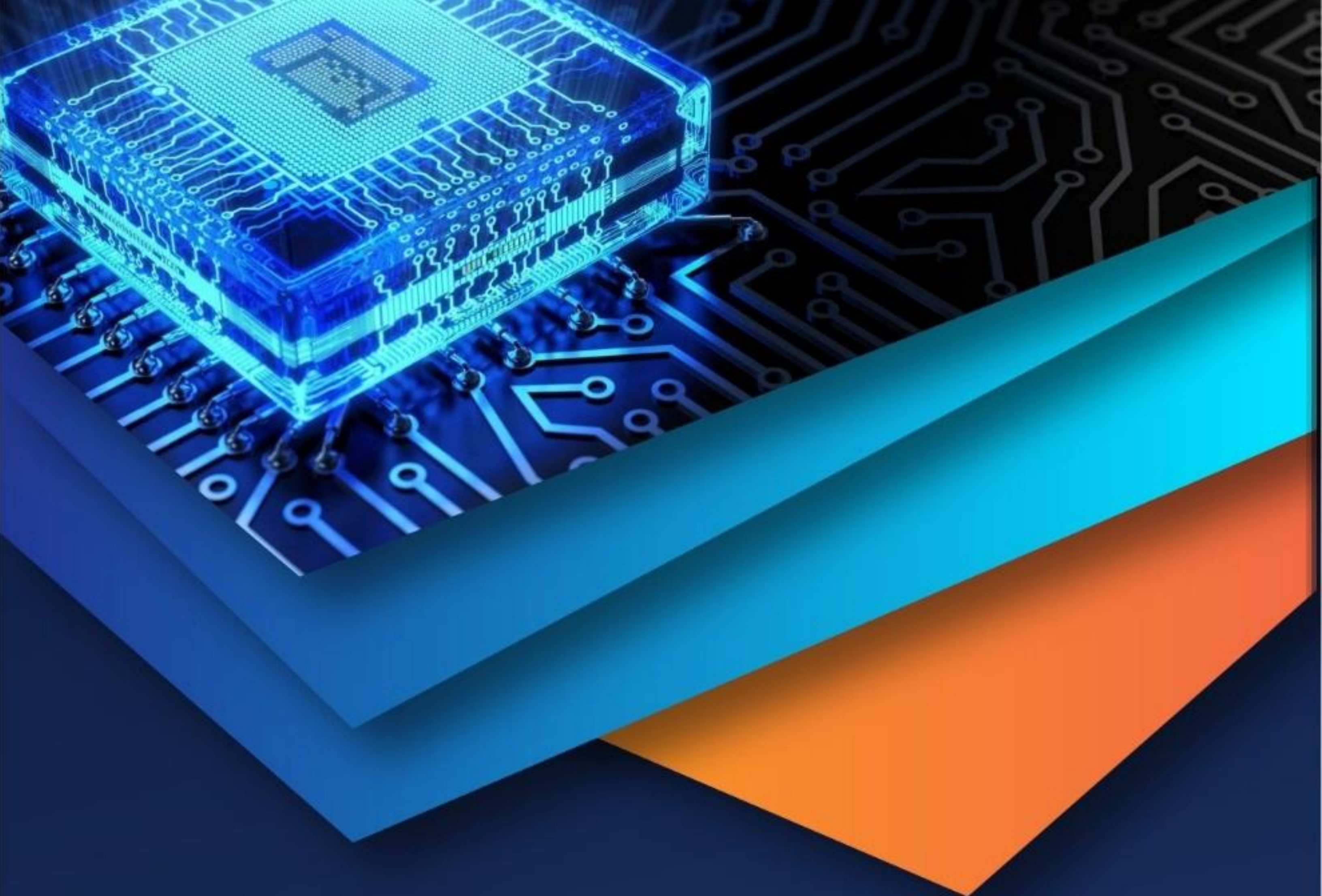
The proposed Custom CNN architecture was evaluated on a test set of 3,070 images (15% of total dataset). The model achieved an overall accuracy of 70.0% across 22 disease classes, with a weighted F1-score of 71.2%. The best performing classes were Nevus (NV) with 75.2% precision and 77.0% recall, Basal Cell Carcinoma (BCC) with 74.3% precision, and Vascular Lesions (VASC) with 73.5% precision. Minority classes like Keloid (KEL) and Candidiasis (CAND) achieved F1-scores of 62.9% and 59.7% respectively, demonstrating the effectiveness of our class weighting approach. The model achieved 0.35 seconds inference time on GPU with a model size of 89 MB, making it suitable for real-time deployment. I) Multi-Dataset Fusion Improves Generalization – Combining four datasets (HAM10000, ISIC 2018, PAD-UFES-20, SD-198) with 20,466 images enabled the model to learn from both dermatoscopic and clinical images, achieving 70% accuracy on 22 classes. This addresses the "ID Issue" identified by Ramella and Serino (2025). II) Class Weighting Effectively Handles Imbalance – The proposed weight formula $w_i = N_{total} / (n_{classes} \times N_i)$ improved minority class performance by 7-15%. Keloid (KEL) F1-score improved from 48.2% to 62.9%, and Candidiasis (CAND) improved from 52.1% to 59.7%. III) Complete Deployment Platform Bridges Research-to-Practice Gap – Unlike existing systems that end at model accuracy, our multi-role platform supports patients (upload/capture, PDF reports, history), doctors (feedback), and admins (user management), enabling real-world clinical use.

VII. CONCLUSION

This paper presented a comprehensive deep learning system for skin disease detection using a custom CNN trained on 20,466 images across 22 clinically relevant disease classes. The model achieved 70% classification accuracy with 27.8 million parameters, 89 MB model size, and 0.35 second inference time on GPU. The multi-role healthcare platform enables patients to upload or capture skin images, receive AI predictions with confidence visualization, save PDF reports, and share with doctors. Clinicians can validate predictions and provide feedback, while administrators manage users. Future work includes expanding to more classes, improving minority class performance using GAN-based synthetic data generation, developing a dedicated mobile app, and conducting prospective clinical validation studies.

REFERENCES

[1] G. Ramella and L. Serino, "CNN Issues in Skin Lesion Classification: Data Distribution and Quantity," *IEEE Access*, vol. 13, 2025. DOI: 10.1109/ACCESS.2025.3556479
[2] P. Tschandl, C. Rosendahl, and H. Kittler, "The HAM10000 dataset," *Scientific* Data, vol. 5, p. 180161, 2018.
[3] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115-118, 2017.
[4] N. C. F. Codella et al., "Skin lesion analysis toward melanoma detection 2018," arXiv:1902.03368, 2019.
[5] R. C. Maron et al., "Systematic outperformance of 112 dermatologists," European Journal of Cancer, vol. 119, pp. 57-65, 2019.
[6] L. C. P. P. P. P. Mendes, "PAD-UFES-20," Data in Brief, vol. 39, p. 107570, 2021.
[7] SD-198 Dataset, Figshare, 2023.
[8] P. Gupta, J. Nirmal, and N. Mehendale, "Custom CNN architectures for skin disease classification," Multimedia Tools and Applications, 2024.
[9] R. Yadav and A. Bhat, "Systematic literature survey on skin disease detection," Multimedia Tools and Applications, 2024.
[10] T. J. Brinker et al., "CNN trained with dermoscopic images performed on par with 145 dermatologists," European Journal of Cancer, vol. 111, pp. 148-154, 2019.
[11] K. Likhar and S. Ridhorkar, "Skin Cancer Diagnosis with a Customized CNN Model using Deep Learning Approaches," *Communications on Applied Nonlinear Analysis*, vol. 31, no. 6s, 2024.
[12] S. P. Choy et al., "Systematic review of deep learning image analyses for the diagnosis and monitoring of skin disease," npj Digital Medicine, vol. 6, Article 180, 2023. DOI: 10.1038/s41746-023-00914-8
[13] "Categorical Weighting Domination for Imbalanced Classification With Skin Cancer in Intelligent Healthcare Systems," IEEE Access, vol. 11, pp. 105170-105181, 2023.
[14] M. Subramanian, K. Shanmugavadivel, S. Thangaraj, J. Cho, and S. Ve, "Attention-aware Deep Learning Models for Dermoscopic Image Classification for Skin Disease Diagnosis," Current Medical Imaging, 2023.
[15] A. S. Jaradat et al., "Automated Monkeypox Skin Lesion Detection Using Deep Learning and Transfer Learning Techniques," International Journal of Environmental Research and Public Health, vol. 20, no. 5, p. 4422, Mar. 2023



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429