DermaCare: AI Driven Skin Disease Detection and Skincare Recommendation System

Usha Kirana S P[1], Ebbali Pavithra[2], Gowrav K M[3]

[1,2,3]Department of Computer Science and Engineering, Don Bosco Institute of Technology, Bangalore, Karnataka, India.

usha14.nayak@gmail.com, ebbalipavithra@gmail.com, gowravkmprofessional@gmail.com

Abstract

Accurately identifying skin diseases can be quite tricky, honestly, since so many of them share similar visual features. This gets even tougher in regions where dermatologists are in short supply. It's a real challenge for both patients and healthcare providers trying to make the right call. To resolve this we developed a system, powered by machine learning and deep learning that classifies five skin conditions, such as acne, rosacea, fungal infections, eczema, psoriasis, and hives, using Convolutional Neural Networks (CNNs). The step by step process: first, clinical and dermoscopic images are preprocessed, then analyzed by a CNN model, and finally paired with a rule based module to generate basic treatment and skincare recommendations. This tool is designed to support both medical professionals and individuals, offering quick and reliable primary diagnoses in resource-limited settings.

Keywords: Deep learning, CNNs, VGG16, skin disease classification, medical imaging.

I. Introduction

Millions of individuals across the globe live with skin disorders; however, it is a significant issue to receive proper and timely diagnoses. The issue is particularly serious in underprivileged populations, wherein there is minimal availability of trained dermatologists. Hence, individuals living in such populations may have to wait for long durations of time or, in certain cases, even rely on unreliable sources for self-diagnosis, which can yield unexpected health outcomes [1]. Psoriasis, eczema, and melanoma may frequently present alike, and their clinical presentation is affected by skin color, making identification problematic without specialized examination [4,6]. Shortage of specialists is an aspect that is responsible for delays in diagnosis as well as treatment and worsening of patient outcomes in large parts of the globe [2,3].

Compounding the problem, many people rely on unverified online tools or subjective self-assessments, which can provide inaccurate results and delay proper care [5]. There's a clear need for smarter, more accessible diagnostic solutions that empower both doctors and patients to detect skin conditions early [7,8].

Recent advances in artificial intelligence and deep learning techniques like CNNs, have been shown to classify skin diseases using images [3,4,6]. Most existing systems only provide a diagnosis without offering practical guidance on what to do next [5,9].

The study suggests an artificial intelligence-driven dermatology assistant to plug glaring loopholes in existing diagnostics equipment. In contrast to the usual systems that can only identify diseases, our system identifies five prevalent skin ailments via the use of convolutional neural network (CNN) image processing and also suggests care recommendations via a rule-based system. The assistant can be used in clinics as well as in homes and is thus especially valuable in areas with restricted access to specialists [1,5,10].

The study is divided into eight main sections. The literature review is given in Segment II, in which we provide an overview of recent developments in the classification of skin diseases. Segment III is about our approach, detailing the process of developing the system. In Segment IV, we compare previous models, their efficacy and

technical approach. Segment V critically evaluates key findings, which have been obtained from research quoted. Finally, Segment VI gives our findings, followed by conflict of interest statements in Segment VII and references in Segment VIII.

II. Literature Review

A. Rashmi et al. presented an AI driven diagnostic system designed for both rapid and precise classification of a wide array of skin diseases. Their methodology leverages deep learning techniques, particularly Convolutional Neural Networks (CNNs), which have become prominent tools in the field of medical image analysis. The system integrates feature extraction, pre-processing, and classification phases, employing a CNN with optimized architecture for detecting inflammatory skin conditions. The model's robustness is validated on a heterogeneous dataset and reportedly surpasses traditional methods in both speed and accuracy. The study emphasizes practical deployment potential in clinical environments by automating the diagnostic process. It also addresses the limitations of manual diagnosis, such as interobserver variability and delay in treatment. The research advocates the role of AI in scalable dermatological diagnostics, improving early intervention and healthcare access [1].

Jeswin et al. developed a machine learning approach designed to differentiate between malignant and benign skin lesions. To address the issue of imbalanced datasets, they incorporated SMOTE, alongside advanced preprocessing techniques, ensuring the model could more accurately distinguish between the two types of lesions.The study utilized a dataset of 15,000 labeled skin images, which were enhanced using techniques such as normalization, image cleaning, and resizing. By reducing misclassification and supporting early detection, the proposed system demonstrates significant potential in minimizing unnecessary treatments. Overall, this work contributes to the implementation of more equitable and dependable AI driven diagnostic tools in dermatology [2].

Priya et al. proposed a low cost, portable diagnostic system using a Raspberry Pi and an ensemble of three CNN models with varying layers for dermatological disease detection. Their system utilizes edge AI to deploy models trained on datasets like HAM10000 and ISIC, achieving an AUC of 0.98 and a F1-score of 94.1%. Advanced pre-processing techniques like hair removal, normalization, and sharpening were applied for robust image clarity. The system demonstrated accessibility and clinical utility in underserved areas. This hardware-assisted diagnostic solution bridges the gap between remote rural care and AI driven dermatological assessment. It highlights the potential of ensemble learning combined with embedded systems for real-world deployment [3].

Juneja et al. presented DERM-AI, a CNN based system that classifies various skin diseases such as eczema, psoriasis, and melanoma with an accuracy of 86.98%. The network employed a preprocessed dataset with image contrast enhancement and feature extraction using CNN layers. Compared to traditional classifiers like SVM and decision trees, DERM-AI showed superior performance. Their model contributes to the automated and scalable detection of dermatological conditions. The study also highlights the relevance of CNNs in real time diagnostic assistance. The results showcase why healthcare requires AI solutions with clearer decision making processes [4].

Navaneeth Bhaskar et al. proposed a hybrid CNN SVM architecture to boost the early diagnosis of skin diseases and offer personalized skincare recommendations. The system utilizes CNN for deep feature extraction from skin images and then classifies those features using an SVM optimized with Particle Swarm Optimization (PSO). The model achieved an impressive accuracy of 95.09%, outperforming traditional methods like KNN and Random Forest. Key steps include image resizing, normalization, and augmentation to improve robustness. The system also offers a user friendly web interface, integrates location based services using Google Maps API, and ensures patient privacy and data security. This approach bridges the gap between accessible skin health diagnostics and modern AI driven precision tools [5].

Kugaraj et al. proposed a comprehensive machine learning structure that predicts not just skin diseases, but also skin tone and skin type, making the solution uniquely holistic in dermatology.

Utilizing CNNs for image analysis and natural language processing (NLP) combined with web scraping, their system offers real time treatment suggestions alongside diagnosis. The model achieved 90% accuracy for disease detection, covering conditions such as eczema, psoriasis, acne, and melanoma. A novel aspect of the work is its integration of up to date skincare recommendations from credible online sources, providing dynamic and personalized insights. The use of diverse datasets also addressed bias related to varying skin tones, further enhancing the system's relevance and inclusivity [6].

Varalakshmi et al. proposed a unified deep learning model that combines Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short Term Memory (LSTM) units to detect and monitor the progression of skin diseases. In their framework, CNNs are used to identify visual patterns from dermoscopic images, while RNN and LSTM components capture the temporal dynamics of disease evolution. This integration allowed the system to not only classify conditions but also track their stages and offer personalized treatment suggestions. Their approach led to a marked reduction in diagnostic errors and proved especially valuable for treating persistent dermatological disorders including eczema and psoriasis, and melanoma. The model's ability to handle both spatial and temporal data gives it a strong edge in supporting long term dermatological care[7].

Singh et al. employed a fine-tuned version of the VGG16 architecture, trained on a sizable dataset of skin disease images obtained from Kaggle. Their model achieved a classification accuracy of 90.1%, with high F1 score and recall, highlighting the effectiveness of deep feature extraction using pre trained networks. By applying transfer learning, they addressed the issue of limited labeled data and successfully distinguished between visually similar conditions. The study reinforces the practical value of transfer learning for early skin disease detection, particularly in data constrained environments. Their solution demonstrates strong potential for use in scalable, real-time dermatological screening tools[8].

Shourie et al. proposed a multiclass CNN based classifier for identifying skin conditions such as eczema, psoriasis, and melanoma using dermoscopy images. The CNN architecture processed images to extract hierarchical features and achieved high classification accuracy. The model's performance highlights CNN's strength in distinguishing dermatological anomalies from benign conditions. It offers a viable alternative to time-consuming biopsy procedures. The work demonstrates how AI can improve diagnostic speed and reduce reliance on invasive testing. This model supports clinical decisions with fast, image based diagnostics [9].

Durgabhavani et al. designed a CNN model trained on thermoscopic skin images for disease classification with over 95% accuracy. The research showed that CNN's layered feature extraction effectively identifies unique heat-based patterns associated with specific conditions. This system was built to aid dermatologists and patients in early self diagnosis. Its success also demonstrated CNN's utility beyond standard RGB images. The authors stress the importance of scalable and accurate AI tools in dermatology. The model can be integrated into smartphone-based diagnosis tools [10].

Murugan et al. focused on classifying skin diseases using clinical parameters via machine learning classifiers, particularly the Naive Bayes algorithm which achieved 98.4% accuracy. The system incorporated a user friendly GUI eengineered for both medical professionals and patients. It included prediction modules for specific age-related conditions such as dermatitis and acne vulgaris. Their work emphasizes accessible and interpretable AI tools for non technical users. This system offers real-world applicability in clinical and rural setups. The focus on GUI integration improves technology adoption by healthcare workers [11].

Shourie et al. conducted a study focused on multi class classification of skin diseases using a pre-trained DenseNet model, applied to dermoscopic images sourced from the HAM10000 dataset. Their model successfully identified seven different types of skin lesions, achieving an accuracy of 88.78%, with individual class performance peaking at 98%. A key strength of this work is its strategic use of dermoscopy a non-invasive, high-resolution imaging method alongside sophisticated data augmentation techniques that helped address class imbalance. The research demonstrates how DenseNet's ability to reuse features across layers enhances its

effectiveness in skin disease classification tasks. Remarkably, the model maintained high accuracy despite limited training data, demonstrating real world applicability[12].

Anggriandi and Sunyoto utilized the ResNet50 architecture to classify seven distinct skin conditions using the HAM10000 dataset, aiming to improve diagnostic reliability through deep learning. Their model delivered strong performance, achieving an accuracy of 91.71%, along with high precision and recall, which highlights its capability to manage complex multi class classification tasks in dermatology. The research addressed key challenges such as class imbalance, the limited availability of dermatological expertise, and the financial burden associated with conventional diagnostic procedures like biopsies. By offering a high performing alternative, their study reinforces the potential of deep learning to support affordable and accessible skin disease diagnosis. This makes it particularly valuable in low resource or remote healthcare environments where traditional solutions may not be attainable[13].

Sarala et al. integrated various machine learning strategies into a deep learning system for multi-class skin disease detection. Their CNN based model targeted both cancerous and non-cancerous conditions, including melanoma, basal cell carcinoma, and benign lesions. By combining texture and color features and implementing vertical image segmentation, the study achieved a recognition rate of over 90%. They also addressed the domain shift issue and class imbalance through advanced techniques like adversarial adaptation and hybrid learning strategies. This approach demonstrates the evolving capabilities of CNNs in generalizing across diverse skin disease datasets[14].

Medishetty Maniraju et al. developed a CNN-based classification system capable of identifying seven types of skin diseases, both cancerous and non-cancerous, using the HAM10000 dataset. The CNN architecture included layers such as Conv2D, MaxPooling, Batch Normalization, Flatten, Dense, and Softmax to perform multi class classification with high accuracy. To enhance performance, the dataset was reordered and augmented through duplication. The system demonstrated promising detection rates, such as 97% for Actinic Keratoses and Melanoma, and above 89% for most other categories. The method is cost-effective and can be deployed as a real time diagnostic and educational tool for dermatology students. The study emphasizes early diagnosis and its role in reducing healthcare burden [15].

III. Methodology

The proposed system follows a modular and scalable AI architecture that integrates deep learning for dermatological diagnosis and a rule-based engine for initial treatment guidance. The workflow is designed to address both the clinical need for accurate visual identification and the practical need for fast, accessible triage support. This section details the technologies, pipeline components, and intelligent decision layers used in the system.

A. Objectives:

The objectives of the proposed system are as follows:

- Build an automated skin condition analysis system that achieves reliable disease identification while seamlessly connecting diagnosis to therapeutic recommendations.
- Utilize a deep learning model, based on transfer learning with VGG16, to identify five common skin conditions from clinical images.
- Implement a robust preprocessing pipeline to standardize input images and enhance model generalization under varied conditions.
- Generate clear, interpretable predictions through a multi-class classification output with associated confidence levels.

- Integrate a rule-based recommendation module to provide users with general treatment or skincare advice tailored to the predicted disease.

A. Technologies and Development Environment:

The system was developed using a combination of modern tools in the fields of artificial intelligence and software engineering. Each component was chosen to ensure high performance, scalability, and ease of development.

1. Programming Language – Python 3.10: Python is widely regarded as the go-to language for machine learning and deep learning because of its simplicity and rich ecosystem. It allows researchers and developers to write readable code while leveraging powerful libraries for data analysis, image processing, and model training.

2. Deep Learning Framework – TensorFlow 2.x and Keras: TensorFlow is an open-source library developed by Google for building and training machine learning modelsKeras, a high-level API built into TensorFlow, simplifies the process of building neural networks by allowing developers to create complex models with fewer lines of code. Together, they offer both ease of use and robust capabilities, making them well-suited for implementing deep learning architectures such as VGG16.

3. Image Processing Libraries – OpenCV and PIL: OpenCV for computer vision tasks and PIL for image manipulation. Together, they perform crucial preprocessing operations including resizing images to standard dimensions, normalizing pixel values, and enhancing key features.This standardization process guarantees consistent image quality for our models, whether the source is a high-end dermatoscope or a smartphone camera in variable lighting conditions.

C. Brief Overview of Machine Learning and Deep Learning:

Machine learning allows systems to learn from examples much like humans do think of how a child gradually learns to distinguish cats from dogs by seeing many examples. Instead of following strict programming guidelines, these models learn patterns from the training data to guide their choices.

Going deeper into it, deep learning replicates the way our brains learn using artificial neural networks. In image analysis in particular, Convolutional Neural Networks (CNNs) work particularly well to identify patterns in vision. They learn more and more to recognize meaningful features from basic edges and textures to intricate shapes in a way similar to how we visually inspect objects.

D. System Overview and Pipeline:

The proposed dermatological diagnostic system is designed on a systematic approach with the vision of synchronizing accessibility, accuracy, and usability. Below is a step-by-step description of the working steps of the system:

1. User Image Upload: The process begins with the user snapping and then uploading a picture of the infected skin area by using the widely available smartphone or any other device. The system has been specifically designed to reduce the reliance on professional imaging devices so that the system can be applied on a large scale.

2. Image Preprocessing:

Streamline the dimensions to our set standards. Normalize the color and lighting parameters. Apply specific improvements to increase readability. This extensive preparation assists our model in operating at maximum input quality.

3. The system uses the VGG16 architecture, which has demonstrated excellent performance in medical image analysis. This model examines each processed image to detect distinctive visual patterns by analysing textures, color variations, and morphological features that characterize different skin conditions.

4. Classification Output (5 Disease Classes): Following are the feature extraction, the system classifies the image into one of five skin disease categories: Acne, Rosacea and Fungal Infections, Eczema, Psoriasis, or Urticaria (Hives). A confidence score is given to each prediction, providing insight into how much the system is sure about the diagnosis which in turn helps both the user and the system to further get improved.

Case Figure	Dermatological Disease Class	Details of Skin Disease Class
	Acne Rosacea	A skin condition characterized by clogged pores, pimples, redness, and visible blood vessels, commonly affecting the face and causing inflammation.
	Fungal infections	Skin conditions caused by fungi, leading to red, itchy, ring-shaped rashes like ringworm.
	Eczema	An inflammatory skin condition marked by itchy, red, and cracked skin, often allergy-related.
	Psoriasis	A chronic autoimmune disorder causing red, scaly skin plaques due to rapid cell turnover.
	Urticaria (Hives)	Sudden, raised, itchy welts that appear and fade quickly on the skin.

Table 1 displays visual examples of five common skin conditions that the DermaCare system is trained to recognize. Each condition is shown with an image, its medical classification, and a brief explanation. Acne Rosacea often presents with redness, small bumps, and visible blood vessels, particularly on the face. Fungal infections typically appear as itchy, red patches that may form ring-like patterns. Eczema is known for dry, cracked, and inflamed skin that can worsen with allergies or irritation. Psoriasis results in thick, scaly patches caused by rapid skin cell turnover, while Urticaria (Hives) is marked by sudden, itchy welts that may come and go quickly. These cases illustrate the visual variety the AI model must be able to accurately interpret.

5. Rule-Based Treatment Recommendation: Beyond simply identifying the disease, the system also provides basic treatment guidance. These recommendations are generated using a rule based approach grounded in standard clinical references, offering users safe, first line suggestions for managing or responding to the identified condition.

6. GUI Display or API Response: Finally, the results are delivered to the user either through an interactive graphical interface (developed using Streamlit) or returned in structured format via an API. This flexibility ensures the system can be used both as a standalone application and as a component integrated into broader digital health platforms

E. Image Preprocessing:

Before uploading images into the CNN, the system has 3 main preprocessing steps:

1. Resizing: Each image is resized into 224×224 pixels to align with the input dimensions of the image required by the VGG16 architecture. This standardization ensures uniform input across the dataset.

2. Normalization: To increase model generalization and reduce overfitting, the training images undergoes various transformations such as random rotations, zooms, flips, and brightness adjustments. These techniques simulate real world variability in user-submitted photos.

3. Noise Filtering: The Techniques like Gaussian blur or denoising filters can be used to minimize background noise and camera artifacts, helping the model focus on the actual skin infected area.

These preprocessing steps altogether improve the model's resilience to changes in lighting, image quality, and background elements, making it suitable for practical, real world use.

F. Classification Output and Confidence Scores:A*fter an* image is processed by the CNN model, it produces a set of probabilities for each of the five predefined skin disease categories. The class with the highest probability is selected as the predicted result. The system also offers the following outputs:

- Displays the most likely skin condition based on the model's analysis.
- Shows how certain the model is about its prediction (e.g., "Eczema – 92.5% confident"). If the confidence level is low, the system may also present alternative possibilities for further consideration.

This layered output helps both users and healthcare professionals understand the reliability of the prediction and decide whether additional consultation is needed.

G. System Interaction Flow:

The system follows a structured, user friendly process that enables seamless interaction between the user and the AI model. The journey begins with image upload and ends with a diagnosis and general care guidance.
The step by step flow is designed to support real world usability in various scenarios:

- Individuals can use the system to quickly evaluate visible skin issues on their own.
- General practitioners can use the tool for preliminary screening before specialist referral.
- The model can assist in basic diagnosis where professional dermatology services are not immediately available.

The Fig 1. Shows the System architecture of the proposed AI based dermatological diagnosis model. The diagram illustrates the sequential flow from user image upload through preprocessing, feature extraction using the VGG16 backbone, multi-class disease classification, and rule-based treatment recommendation. The system is designed to ensure accurate skin condition identification and provide general care suggestions based on the classified output. The flowchart highlights the interaction between user input and model response, supporting accessible and timely skin health assessment.

The system begins by asking users to upload a clear image of the affected skin area. It then checks the quality of the image, ensuring it's not blurry. After validation, the image is preprocessed through resizing and enhancement steps to prepare it for analysis. The VGG16-based CNN model extracts key features from the image, which are used to classify the skin condition into one of five categories. Depending on the confidence level of the prediction, the system may suggest further action like retaking the image or consulting a doctor.

Finally, a treatment suggestion is generated, and results are displayed with guidance and an option for user feedback.

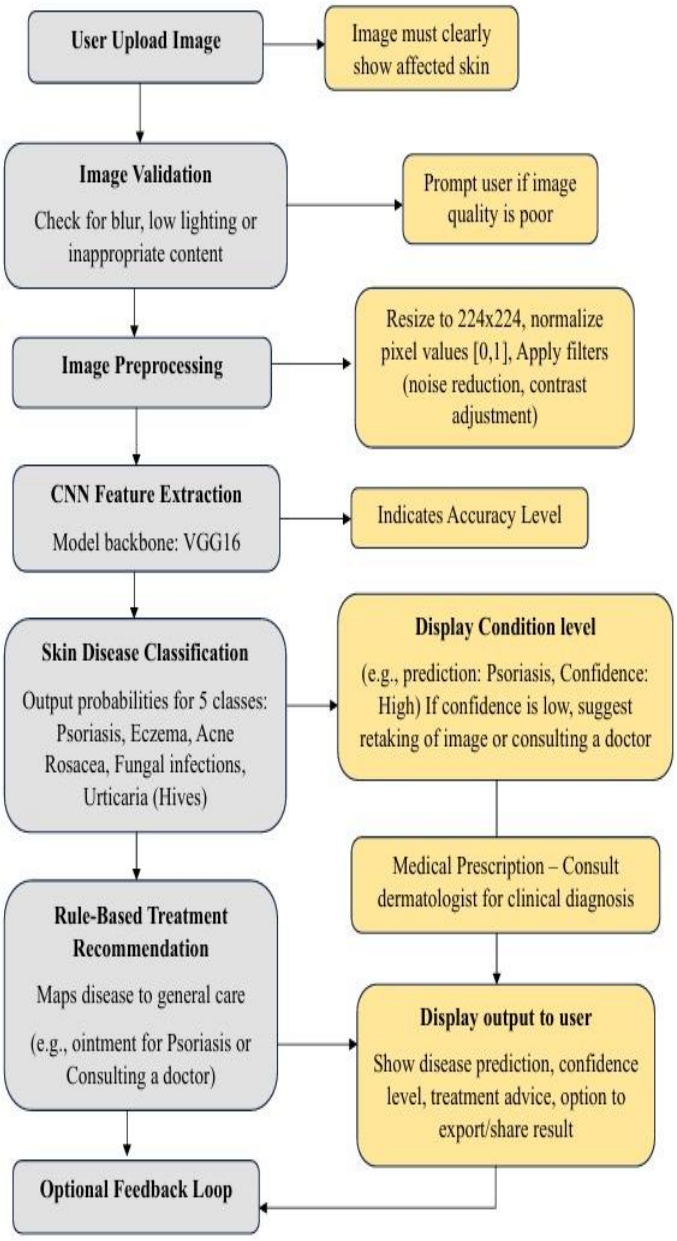


Fig 1: Proposed System Framework

IV. Comparative Analysis

Table 2 provides a comparative overview of recent studies that focus on classifying skin diseases using a variety of machine learning and deep learning methods. The analysis evaluates five key research works based on factors such as author names, techniques employed, datasets used, reported accuracy, benefits, and limitations. These methods span from conventional algorithms like K-Nearest Neighbors (KNN) and Naive Bayes to more robust deep learning architectures such as ResNet50 and DenseNet. While each approach showcases unique strengths ranging from high classification accuracy to personalized treatment recommendations and robustness in handling multiple classes they also encounter limitations like dependence on large datasets, sensitivity to image quality, and lack of interpretability. Overall, the table underscores the rapid advancements and diverse strategies emerging in AI-powered dermatological diagnosis.

Table 2: Comparative Analysis of AI-Based Models for Multi-Class Skin Disease Diagnosis

SL.No	Author Name	Year	Method Used	Advantage	Limitation	Dataset Used	Accuracy
1	Suganya K. et al.	2024	CNN + NLP + Web scraping	Multi-input diagnostic system; personalized recommendations	Dependent on web scraping quality and NLP accuracy	Custom + online data	90%
2	Poonam Shourie et al.	2023	DenseNet (pre-trained)	Superior feature reuse and learning efficiency; good for dermoscopy data	Sensitive to image quality; model interpretability is lower	HAM10000	88.78% (overall), 98% (per class)
3	Boddupelli Durgabhavani et al.	2023	CNN	High classification performance; supports thermoscopic image analysis	Sensitive to noise and variations; lacks explainability	Thermoscopic images	95% (classification), 90% (validation)
4	Suganiya Murugan et al.	2023	KNN, Naive Bayes	GUI-based easy interface; suitable for low-resource settings	Lower generalization in large-scale real image classification	Clinical parameters	98.4% (Naive Bayes)
5	Dendi Anggriandi et al.	2023	ResNet 50	High precision, recall, and balanced F1-score; robust multi-class support	Requires large, balanced dataset and complex preprocessing	HAM10000	91.71%

V. Result Analysis

To better grasp the current direction of research in AI-driven skin disease diagnosis, fifteen recent papers were examined. These works were grouped based on their core methodologies, such as CNN based architectures, transfer learning, hybrid approaches, and deployment through real-time or web platforms. The purpose of this

evaluation is to showcase commonly adopted techniques while also pointing to areas that hold potential for further study. Figure 2 illustrates this categorization, providing a clear overview of how different technological strategies are being applied in the field.

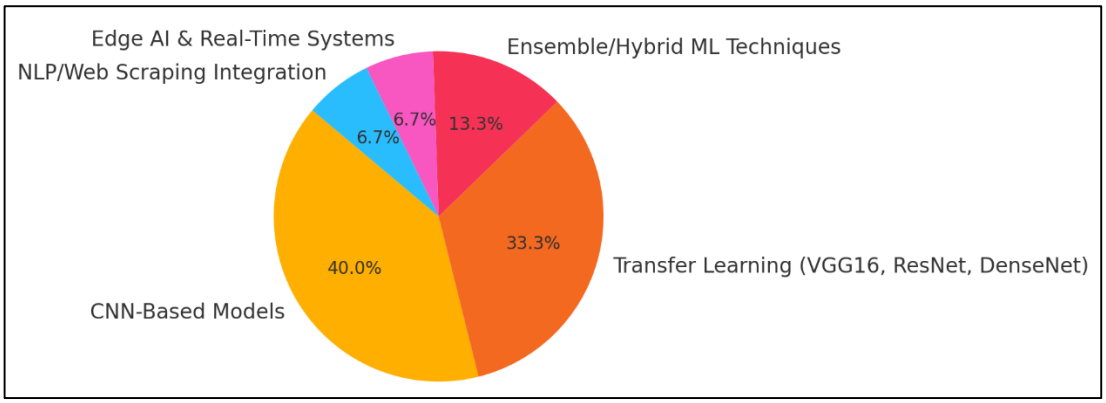


Fig 2: Research Focus Distribution Among Surveyed Papers

VI. Conclusion

Skin diseases remain a big concern, with substantial impact on individuals' physical, mental, and social well-being. In many cases, dermatological conditions are also indicative of underlying systemic disorders, underscoring the importance of early detection and accessible diagnostic support. This research paper represents a conceptual framework for an AI-based dermatological diagnosis system designed to assist in identifying common skin conditions and offering basic care guidance.

By combining a deep learning model (VGG16) with a rule based treatment recommendation module, the system aims to bridge the gap between skin disease detection and immediate patient support.

The primary focus of this work is to address the real-world challenges of delayed diagnosis, limited access to dermatologists, and the lack of clear next steps for patients after an initial concern. The proposed approach simplifies the process from image upload to diagnosis and basic advice into a single, user-friendly flow. This makes it ideal for inclusion in mobile health apps, teleconsultation platforms, and community health tools.

The proposed work envisions an AI powered assistant that combines technical intelligence with practical care, aiming to make dermatological screening more approachable, timely, and impactful for users everywhere.

VII. Conflict of Interest Statement

The authors have no conflict of interest to disclose.

VIII. References

[1] A.Rashmi, N. R. T., and A. A. S., “AI-Powered Dermatological Diagnosis for Diverse Skin Diseases,” Proceedings of the International Conference on Innovative Systems for Cybersecurity(ISCS),2024,pp.1–5.DOI: 10.1109/ISCS61804.2024.10581357.

[2] J. P. Pandian, R. Jegan, R. Jerlinkasmir, P. S. H. Jose, and P. A. Christu Raj, “Early Detection and Treatment of Skin Diseases Using Advanced Image Preprocessing and Machine Learning Techniques,” Proceedings of the 4th International Conference.on Ubiquitous Computing and Intelligent Information Systems (ICUIS), pp. 1031–1037, 2024. DOI: 10.1109/ICUIS64676.2024.10866949.

[3] E. Priya, N. Vishnu V, L. Kamal T. M, and A. Aakash, "Optimizing Convolutional Neural Networks for Dermatological Disease Detection Using Ensemble Learning on Edge AI Platforms," Proceedings of the International Conference Power, Energy, Control and Transmission Systems (ICPECTS),pp.1–6,2024.DOI: 210.2024.10780196.

[4] S. Juneja, P. Tiwari, R. Devi, and S. Atwal, "DERM-AI: A Convolutional Neural Network Based Approach for Skin Disease Detection," Proceedings of the International Conference on Intelligent Systems for Cybersecurity (ISCS), pp. 1–6, 2024. DOI: 10.1109/ISCS61804.2024.10581357.

[5] N. Bhaskar, B. R. Devi, S. R. Raghurama, B. Umesh, N. T. Attavar, and S. V. Kambli, "Skin Disease Identification and Skincare Solutions Using Deep Learning Approach," 2024 International Conference on Integrated Intelligence and Communication Systems (ICIICS), 2024, pp. 1–7, doi: 10.1109/ICIICS63763.2024.10859493.

[6] L. Kugaraj, D.M.G.T. Dassanayake, and K. Rajendran,"A Machine Learning Framework for Accurate Skin Tone, Type, and Disease Detection with Web Scraping and NLP for Dermatological Insights,"2024 9th International Conference on Information Technology Research(ICITR)2024,pp.1-6,DOI:10.1109/ICITR64794.2024. 10857787

[7] K. Varalakshmi and A. Revathi, "Computer-Aided Design for Skin Disease Identification and Categorization Using Deep Learning," Proceedings of the 7th International Conference on Image Information Processing (ICIIP), pp. 374–379, 2023. DOI: 10.1109/ICIIP61524.2023.10537681.M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[8] G. Singh, K. Guleria, and S. Sharma, "A Transfer Learning Based Pre-trained VGG16 Model for Skin Disease Classification," Proceedings of the IEEE Mysuru Conference,pp.1–6,2023.DOI: 10.1109/Mysuru Con59703.2023.10396942.

[9] P. Shourie, V. Anand, and S. Gupta, "AI-Based Multiclass Classification of Skin Diseases in Dermoscopy Images Using Convolutional Neural Network," Proceedings of the IEEE World Conference on Communication & Computing (WCONF),pp.1–5,2023.DOI: 10.1109/WCONF58270.2023.1 0235191.

[10] B. Durgabhavani, B. Chandana, S. Sandhyarani, G. Lavanya, G. Srikanth, and N. Bhaskar, "Classification of Skin Disease using CNN," Proceedings of the International Conference on Evolutionary Algorithms and Soft Computing Techniques (EASCT),pp.1–5,2023: 10. 1109/EASCT59475.2023.103 93477.

[11] S. Murugan, S. R. Srividhya, S. P. Kumar, and B. Rubini, "A Machine Learning Approach to Predict Skin Diseases and Treatment ecommendation System," Proceedings of the 5th International Conference on Smart Systems and Inventive Technology(ICSSIT),pp.1157 1161,2023.DOI:10.1109/IC SSIT5814.2023.10061150.

[12] P. Shourie, V. Anand, and S. Gupta, "Multi-class Classification of Skin Diseases using Pre-trained DenseNet Architecture on Dermoscopy Images," 2023 International Conference on Applied Intelligence and Sustainable Computing (ICAISC), 2023, pp. 1–7, DOI: 10.1109/ICAISC58445.2023.10199421

[13] D. Anggriandi and A. Sunyoto, "Multi-Class Classification of Skin Diseases Using ResNet50," 2023 6th International Conference on Information and Communications Technology(ICOIACT),2023,pp.349–354,DOI: 10.1109/ICOI ACT59844.2023.10455 953.

[14] Sarala, B., Suganthy, M., Chebian, W.T., SathyaSri, B., Hepzhipah, J.J., Perarasi, M., & Akshaya, K. (2023). "Integrating Advanced Machine Learning Techniques for Multi-Class Skin Disease Diagnosis".Proceedings of the International Conference on Research Methodologies in Knowledge Management, AI and Telecom Engineering (RMKMATE 2023), IEEE, doi:10.1109/RMKMATE59243.2023.10368995.

[15] M. Maniraju, R. Adithya, and G. Srilekha, "Recognition of Type of Skin Disease Using CNN," 2022 First International Conference on Artificial Intelligence Trends and Pattern Recognition(ICAITPR),2022,pp.1–6,DOI: 10.1109/ICAITPR51569.2022.9844199.

Copyright & License:
© Authors retain the copyright of this article. This work is published under the Creative Commons Attribution 4.0 International License (CC BY 4.0), permitting unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.