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Convolutional Neural Network-Driven Early Detection of Dermatological Disorders in a Clinical Bioscience Framework

Girish Talmale

Department of Computer Science and Engineering, G H Raisoni College of Engineering, Nagpur, India

Keywords: Dermal disease diagnosis, Deep learning, Convolutional Neural Networks, Dermal image classification, Performance Evaluation

Abstract

One of the most prevalent health problems in the world is skin disorders, which frequently call for an early and precise diagnosis to avoid complications. An AI-based method for the initial diagnosis of dermatological symptoms is presented in this work. The program interprets medical photos of skin lesions and uses improvements in deep learning and machine learning to analyse symptoms and make recommendations for a diagnosis. A wide range of skin disorders, including melanoma, psoriasis, and eczema, were considered. The technology integrates convolutional neural networks (CNNs) for the image classification approach for diagnosis. The AI tool continuously learns from fresh data inputs, advancing its diagnostic accuracy over time. The ultimate objective is to offer a scalable, affordable, and user-friendly diagnostic tool to support dermatologists in their practice.

Introduction:

Skin illnesses pose a huge worldwide health burden, impacting millions of people regardless of age, gender, or geographical location. These illnesses can be anything from mild irritants like eczema and acne to potentially fatal diseases like melanoma, a severe form of skin cancer. Numerous factors, including genetic predisposition, environmental factors, allergens, infections, autoimmune reactions, and lifestyle choices, can contribute to the development of skin diseases. Skin disorders can be made worse by elements like pollution, exposure to ultraviolet (UV) radiation, dietary decisions, and hormone abnormalities. Skin-related symptoms can occasionally be the result of underlying medical illnesses like diabetes or immune system issues, which can make diagnosis and treatment more difficult.

Skin disease management and therapy depend heavily on an early and precise diagnosis. However, because of the wide range of presentations, overlapping symptoms, and the need for specialist knowledge, identifying dermatological disorders can be difficult. Patients frequently experience delays in diagnosis in underserved or dermatologist-poor areas, which exacerbates their disease. Even in well-equipped healthcare systems, dermatologists may have difficulty recognising rare or unusual skin disorders, leading to misdiagnoses or inappropriate treatments.

Interest in using artificial intelligence (AI) in dermatology has grown as a result of the field's expanding demand for dependable and effective diagnostic assistance systems. Artificial intelligence (AI) has the potential to completely transform dermatological diagnostics by offering quicker, more accurate evaluations. AI is capable of processing enormous volumes of data and spotting intricate patterns. As a subset of artificial intelligence (AI), machine learning (ML) allows computers to learn from massive datasets. This allows for the development of diagnostic models that can analyse dermatological images and spot patterns that human eyes would miss. Deep learning (DL) methods, in particular convolutional neural networks (CNNs), have demonstrated remarkable potential in medical image analysis and are incredibly well-suited for picture categorisation tasks. Large datasets of tagged photos are used to train these models so they can distinguish between different skin states. As they are exposed to more data, their accuracy increases steadily. Additionally, by combining textual and image-based data inputs, AI can help with natural language processing (NLP), which can help analyse patient symptoms and support diagnostic decision-making.

Among the many benefits of AI-based diagnostic systems is their rapid and economical provision of preliminary diagnosis. These instruments can fill the void in dermatological care in areas where specialists are

*Corresponding Author: girishitalmale@gmail.com

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overworked or unavailable. Artificial intelligence (AI) solutions enable patients and general practitioners to take proactive measures in controlling skin diseases by providing immediate feedback based on the input of skin photos and symptoms. They also assist in lessening the load of diagnosis on healthcare systems, allowing dermatologists to concentrate on more complicated situations.

Additionally, by reducing human error, standardising diagnostic protocols, and regularly updating diagnostic models with updated medical data, the incorporation of AI into dermatology can enhance clinical decision-making. Because AI can accurately process and understand large, complicated datasets, it can also spot tiny trends that point to uncommon or recently discovered disorders. This is in favor of early detection, which is essential for diseases like melanoma, for which prompt treatment greatly enhances patient outcomes.

In summary, AI has the power to revolutionise dermatological diagnostics by enhancing its speed, accessibility, and accuracy. With the development of strong artificial intelligence algorithms, dermatology stands to gain from an intelligent support system that increases access to prompt and efficient treatment for skin-related illnesses while enhancing the knowledge of medical practitioners.

Literature Survey

Numerous attempts have been made by researchers to detect dermal lesions. Some of the key similar research was discussed in this chapter.

Researchers have conducted extensive research on cutaneous lesion detection. This chapter covered a few of the most important comparable studies.

Ojha *et al.* (2022) made major contributions to the field of AI-based dermatology with their study focusing on the classification and detection of skin disorders. The authors stress how critical it is to treat the various kinds of skin conditions brought on by both internal and external variables. Their work develops an early-warning tool for skin disease identification by combining deep learning classifiers with image processing techniques.

Convolutional neural networks (CNNs) and Mobile Net, a lightweight neural network built for resource-constrained situations, were the two main classifiers used in their methodology. Because CNNs can automatically extract significant characteristics from images using several convolutional layers, they are frequently employed in image-based applications. However, MobileNet is particularly effective in mobile and embedded vision applications because it is tailored for these types of applications.

The goal of Chowdary *et al.* (2023) was to create a cloud-based application that would combine computer vision, deep learning, and cloud computing to identify different skin conditions brought on by bacteria, fungi, viruses, and environmental variables. The research employed generative adversarial networks (GANs) in conjunction with an ensemble of convolutional neural networks (CNN) and computer vision techniques to construct a model that can identify diseases based on symptoms, skin-related photos, and videos. Apart from identifying diseases, the app has a recommendation engine built with Amazon Personalise that makes recommendations for treatment plans, prescription drugs, and preventive measures for every ailment that has been identified.

The application of diverse computer vision-based deep learning techniques to the prediction of various skin and breast illnesses was investigated by Parashar et al. (2022). In order to develop a productive PC-assisted framework that may help patients and medical professionals diagnose these illnesses, the research set out to assess a number of well-known algorithms. Utilising the Coimbra dataset from the UCI AI data bank, the study enhanced classification methods by combining knowledge gain and local binary patterns (LBP) to the data for feature extraction. Support vector machines (SVM), Random forests, recurrent neural networks (RNN), and convolutional neural networks (CNN) were among the classifiers used in the study for comparison. These results imply that deep learning algorithms, in particular RNNs, have promising success rates when it comes to identifying malignant tumours and other disorders.

Ramya *et al.* (2022) concentrated on the use of image processing methods for the diagnosis of skin disorders, with an emphasis on third-world nations where early detection tools are frequently deficient. The study demonstrates how melanocytes in the skin create melanin, which absorbs UV rays and, if unregulated, can cause skin damage and cancer. The study made use of image segmentation techniques to help identify different skin diseases based on a collection of photos. Image preprocessing techniques, including noise reduction and deblurring, were used before categorisation. The study focused on skin conditions like melanoma, acne, dermatomyositis, candidiasis, cellulitis, scleroderma, chickenpox, ringworm, eczema, and psoriasis, highlighting the serious health hazards associated with delaying treatment for these conditions.

Ajith *et al.* (2017) skin disease diagnosis approach is very accessible, particularly in rural places, as it uses image processing techniques and is optimised for mobile devices. The patient simply needs to provide a photograph of the skin area that is afflicted, and the system takes care of the rest to diagnose the disease. This makes the method fully noninvasive. This method offers a practical and affordable alternative for the early detection and diagnosis of skin diseases, and it is especially helpful in rural areas with limited access to dermatologists. Because the system is

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transportable in design, it requires less infrastructure to provide healthcare services to underserved populations.

The application of image processing methods to support skin disease identification was investigated by Roy *et al.* (2019). The study emphasises the significance of receiving treatment for skin illnesses as early as possible because postponing treatment can have fatal consequences or cause serious health issues, including acne, dermatomyositis, candidiasis, cellulitis, scleroderma, chickenpox, ringworm, eczema, and psoriasis. The authors used a variety of image processing techniques, such as morphology-based picture segmentation, adaptive thresholding, edge detection, and K-means clustering, to address this. The set of images underwent pre-processing to eliminate noise and deblur before segmentation methods were implemented. From the input image, the system could determine the state based on distinct patterns linked to various skin conditions.

An image-based application for diagnosing skin diseases on mobile devices that can recognise skin problems from photos of diseased skin was shown by Kumar *et al.* (2023). The algorithm compares pre-processed photographs and determines threshold value differences in order to analyse a set of photos and identify illnesses. When questionable skin anomalies are found, these threshold deviations are taken into consideration when making decisions. The machine learning technique was implemented in the program using the Open CV library, which was developed for the Android platform. According to the research, there is a growing number of Android-based mobile applications available for the diagnosis of skin infections. These applications offer a convenient and approachable means of detecting skin diseases, especially in places where dermatologists are not readily available.

To accurately detect skin illnesses, Swamy *et al.* (2021) concentrated on employing texture and colour criteria such as smoothness, coarseness, and regularity. In order to construct a machine learning method, the study investigated variance, entropy, and the maximum histogram value of Hue-Saturation-Value (HSV) colour features. Support Vector Machine (SVM) and Decision Tree (DT) models were used in the algorithm's development. To find texture-based leaf nodes in the Decision Tree, variance was used at the second level, while entropy was utilised as the first-level split criterion. The greatest HSV histogram value was utilised to further divide the tree for colour-based attributes. The efficacy of the suggested algorithm in classification tasks was assessed by looking at how accurately it diagnosed skin conditions.

The difficulties with conventional skin cancer detection techniques, which frequently entail drawn-out and time-consuming procedures carried out by medical specialists like doctors or dermatologists, were brought to light by Shasim *et al.* (2023). The authors suggested an automated method that combined artificial neural networks with image processing and computer vision techniques to overcome these difficulties. These techniques can still require a lot of resources to implement, even though they can save costs and increase prediction accuracy. The authors of the study presented a Convolutional Neural Network (CNN) model for skin disease classification that is based on deep learning. They assembled a large dataset of about 2,102 photos from several repositories, concentrating on dermatoscopic photos of pigmented lesions, in order to train their suggested model. The intricacy and diversity of skin disorders, which can exhibit a spectrum of symptoms and severity levels, from mild to severe, and can be impacted by situational or genetic variables, were examined by Dwivedi *et al.* (2021). This variety presents difficulties for healthcare providers who are responsible for identifying and treating these disorders, as well as for patients who may find it difficult to define their symptoms. Certain skin conditions can become serious or even fatal if they are ignored or managed poorly. The authors stressed the urgent need for a rapid screening system for skin problems in order to reduce these dangers. Their research offers a novel approach to precisely identify skin conditions using deep learning technology. In particular, they applied proper annotation and developed the Fast R-CNN architecture.

Methodology

The existing approaches to skin disease diagnosis often exhibit various drawbacks, such as relying on manual examinations and the inaccessibility of dermatological facilities in distant places. Due to their heavy reliance on expert assessments, many conventional approaches have the potential to bring subjectivity and variability into the diagnosing process. Moreover, early detection attempts are complicated by the absence of scalable technologies that can handle the wide diversity of skin diseases. In order to overcome these obstacles, we suggest an automated system that improves the precision and effectiveness of skin disease categorisation by utilising cutting-edge deep learning techniques, namely Convolutional Neural Networks (CNN) and MobileNet networks.

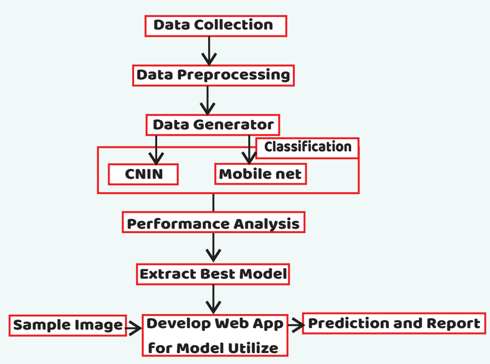

Figure-1 : Flow diagram - proposed system

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As illustrated in Fig.-1, our proposed approach begins with data collection, where a comprehensive dataset of skin images is gathered, focusing on various dermatological conditions. Fig.-1 describes the system architecture. The architecture represents a system designed for skin cancer detection, structured in three main layers: Presentation, Logical, and Data.

In the Presentation Layer, users can register or log in to access the system, allowing doctors or patients to create accounts. Once logged in, users can enter patient information, such as symptoms or images of skin lesions. After entering the data, the system processes it to detect any potential signs of skin cancer. Finally, the results are displayed to the user, indicating whether skin cancer is present or not.

The Logical Layer focuses on the underlying processes that support the application. It includes an authentication feature that ensures only authorised users can access the system. The layer also encompasses the training of the Convolutional Neural Network (CNN) model, which learns from the training data to recognise patterns associated with skin cancer. Following the training, the model is validated to ensure its accuracy before being utilised for real patient data. The skin cancer detection function applies the trained model to analyse new patient information.

In the Data Layer, various databases are maintained to support the system's functionality. This includes storing all administrative and patient-related information, as well as the training data used to develop the model. The trained model itself is also stored in this layer, representing the final version that is ready for use in detecting skin cancer in new patient data.

Overall, this architecture organises the system into clear functional areas, facilitating secure user access, effective model training and validation, and efficient data management for skin cancer detection.

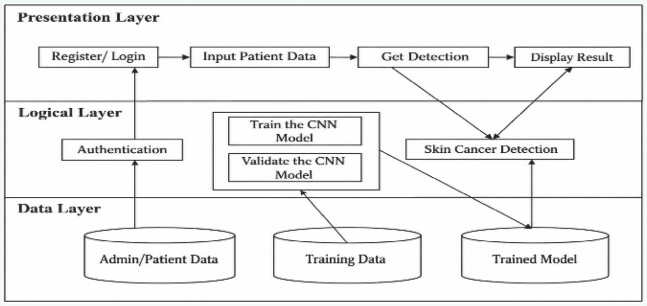

Figure 2: System architecture - proposed system

This data undergoes preprocessing to ensure quality and consistency, involving steps such as normalisation, resizing, and augmentation to enrich the dataset and mitigate overfitting. Subsequently, a data generator is employed to efficiently feed the processed images into the model during training.

The core of our methodology involves the classification phase, where two distinct models, CNN and Mobile Netare utilized. The CNN model is particularly effective in capturing spatial features in the image data, while the MobileNet model excels at recognising patterns in sequential data. This dual approach allows us to evaluate and compare the performance of each model in diagnosing skin diseases.

Some convolutional, pooling, and fully connected layers are used in the construction of the CNN model for classifying skin diseases. An input layer that processes images of a fixed size is the first layer in the design. Multiple convolutional layers are then used to extract spatial characteristics, and each one is combined with ReLU activation to add non-linearity. Max pooling layers downsample the feature maps following each convolution in order to reduce dimensionality and concentrate on the most crucial features. The use of batch normalisation helps to accelerate and stabilise training. The learned characteristics are aggregated in the last fully connected layers, which culminate in a multi-class classification softmax output layer. The network can learn hierarchical patterns thanks to its structure, which makes image-based disease diagnosis much more efficient.

Finally, the selected model is integrated into a web application that facilitates user-friendly access to the skin disease classification system. This application aims to empower both healthcare professionals and individuals by providing rapid and accurate diagnoses, thereby improving early detection and preventive care for skin diseases. Through this systematic and innovative methodology, we aim to contribute significantly to the field of dermatology and enhance healthcare accessibility.

Result and Analysis

Using a carefully selected HAM10000 dataset from the Kaggle platform, we conducted a thorough assessment of both Convolutional Neural Networks (CNN) and MobileNet networks for our skin disease classification models. About 10015 photos from various archives made up the dataset, which was mostly composed of microscopic photos of different pigmented lesions and skin disorders. To provide precise model validation and training, every image was carefully annotated. The OpenCV library was used for image processing tasks, and TensorFlow and Keras libraries were used for model implementation in the Python environment used for the experimental setup.

To improve model generalisation, we used strict data preprocessing methods such as image scaling, normalisation, and augmentation. As can be seen from the data, the CNN model outperformed the MobileNet model, which had an accuracy of 80.5%, by achieving an astounding 88.9% training accuracy.

This metric evaluates how often the model's top prediction is correct. It shows the overall classification accuracy of the model. (Fig.-3)

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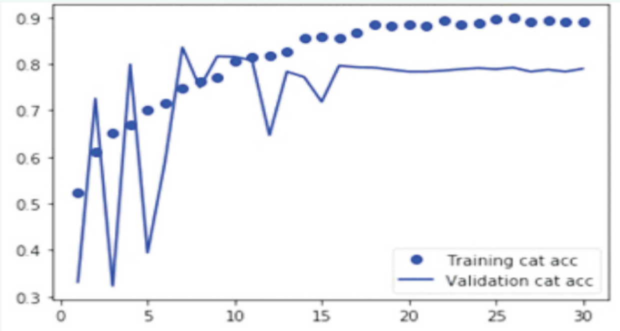

Figure 3: Training and validation accuracy

Top-2 accuracy measures how frequently the correct class is within the model's top two predictions, indicating how well the model ranks the true class. (Fig.-4)

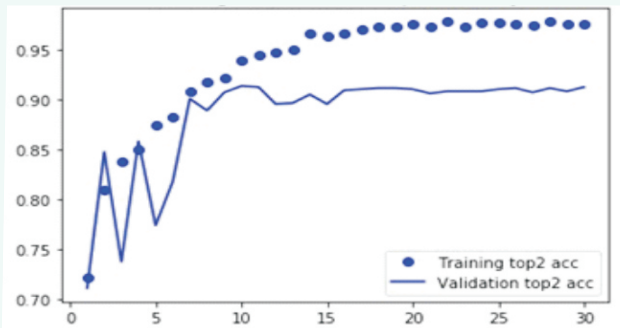

Figure 4: Training and validation top2 accuracy

This metric extends the accuracy check to the top three predictions, showing how often the true class appears among the top three predicted classes. (Fig.-5)

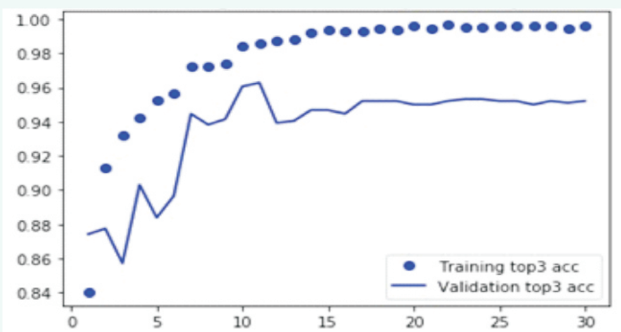

Figure 5: Training and validation top3 accuracy

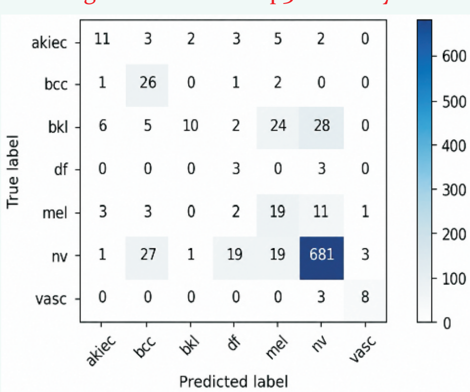

Figure 6: Confusion matrix

The confusion matrix displays the number of correct and incorrect predictions for each class, giving a detailed breakdown of model performance across classes. (Fig.-6)

This measures the difference between the predicted output and the true output during training and validation. Lower loss values indicate better model performance. (Fig.-7)

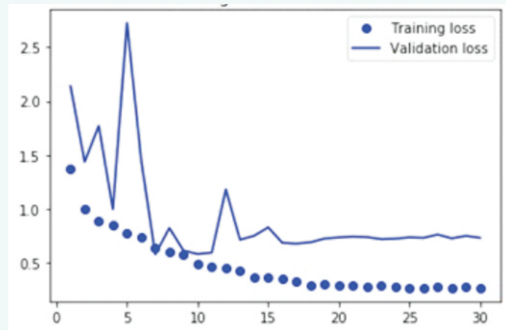

Figure 7: Training and validation loss

To improve model generalisation, we used strict data preprocessing methods such as image scaling, normalisation, and augmentation. To give a comprehensive picture of the effectiveness of the model, we concentrated on accuracy, precision, recall, and F1-score as performance indicators. As can be seen from the data, the CNN model outperformed the MobileNet model, which had an accuracy of 80.5%, by achieving an astounding 88.9% training accuracy.

The training accuracy curve in the graph shows that the model is successfully gaining knowledge from the training set. Initially, there may be rapid gains in accuracy, but as the epochs advance, the curve begins to plateau, showing that the model is nearing its optimal performance on the training set.

Table-1: Performance comparison

Description	MobileNet	CNN
Training accuracy	80.5%	88.9%
Validation accuracy	78.7%	86.5%
Test accuracy	79.6%	84.5%

The testing accuracy ultimately stabilises at around 84.5%, confirming the model's capability to generalise well to unseen data. It's crucial that the testing accuracy remains close to the training accuracy, which indicates that the model is not overfitting. Any significant divergence between the two curves could suggest overfitting, where the model performs well on training data but poorly on unseen data. Additionally, the graph may include loss curves for both training and testing, where a decrease in loss over epochs corresponds to improvements in accuracy. The loss curves typically decrease steadily, indicating that the model is minimising the error between the predicted and actual outcomes. Overall, this graph demonstrates the effectiveness of the CNN architecture in accurately classifying skin diseases, highlighting its potential for real-world applications in dermatology.

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When compared to MobileNet sequential processing, the CNN's architecture was better at extracting features from the images by effectively capturing complex patterns and spatial hierarchies. This performance analysis emphasises the CNN's potential as a strong tool in the early detection and diagnosis of skin disorders, ultimately contributing to improved patient care and outcomes. The results also imply that more improvements, including adjusting hyperparameters and investigating transfer learning strategies, can produce even greater results in subsequent cycles.

Conclusion

This study concludes that deep learning methods, namely CNN and MobileNet units for convolutional and recurrent neural networks, are effective in treating skin conditions. With an astounding 84.5% test accuracy, the results show that the CNN model performs better than the MobileNet. This remarkable degree of precision highlights CNNs' capacity to reliably identify complex patterns and characteristics in skin pictures, which is essential for accurate illness classification. The study also emphasises how crucial it is to use a varied dataset that includes a range of skin states in order to improve the model's robustness.

The suggested method not only makes early detection easier, but it also helps medical practitioners make well-informed judgments about patient care. We can greatly enhance patient outcomes and lessen the strain on healthcare systems by incorporating cutting-edge deep learning techniques into the diagnosis of skin diseases. Subsequent research endeavours could centre on enhancing the model's functionality and investigating its suitability in actual clinical contexts, ultimately leading to more affordable and effective dermatological treatment.

The suggested method not only makes early detection easier, but it also helps medical practitioners make well-informed judgments about patient care. We can greatly enhance patient outcomes and lessen the strain on healthcare systems by incorporating cutting-edge deep learning techniques into the diagnosis of skin diseases. Subsequent research endeavours could centre on enhancing the model's functionality and investigating its suitability in actual clinical contexts, ultimately leading to more affordable and effective dermatological treatment.

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