Chapter 8

Book Chapter

Skin Disease Prediction Using Deep Learning

Mudasir Rashid *[1] and Abhishek Gowda M †[2]

[1]Assistant Professor, Department of MCA, Acharya Institute of Technology, Bangalore, India
[2]Department of MCA, Acharya Institute of Technology, Bangalore, India

Abstract

Diagnosing skin diseases can be a tricky business, requiring a lot of expertise and time. But what if we told you there's a way to make it faster and more accurate? Our research explores the use of deep learning to predict skin diseases, and the results are promising. We trained a special type of computer program called a convolutional neural network (CNN) to look at pictures of skin lesions and figure out what's going on. By feeding it a huge dataset of images, the CNN learned to recognize patterns and features that distinguish one skin condition from another. To make it even better, we used some clever tricks like transfer learning and data augmentation to fine-tune the model. By the use of attention mechanism and multidimensional fusion model became more efficient. This means that doctors could soon have a powerful tool to help them diagnose skin conditions quickly and accurately. Our research shows that deep learning has the potential to revolutionize the way we diagnose skin diseases. With this technology, doctors can make more accurate diagnoses, and patients can get the treatment they need sooner.

Keywords: Deep Learning. Pattern Recognition. Image Processing. Skin Disease Classification.

*Email: mudasir2821@acharya.ac.in Corresponding Author
†Email: gowdamabhishek@gmail.com

1 Introduction

Skin diseases are a growing concern worldwide, affecting millions of people every year (Carniciu et al., 2023). From acne and eczema to skin cancer and rare genetic disorders, the impact of skin conditions on quality of life can be devastating. In the United States alone, skin diseases account for over 50 million doctor visits annually, with treatment costs exceeding $40 billion. In US healthcare and cancer in particular constitutes atlest 173 dollars (Bateni et al., 2023). Despite the alarming statistics, diagnosing skin diseases remains a significant challenge, even for experienced dermatologists. Traditional methods of skin disease diagnosis rely heavily on visual examination, medical history, and laboratory tests. However, these approaches have their limitations. Visual examination can be subjective, and even experienced dermatologists can misdiagnose conditions. Medical history and laboratory tests can be time-consuming and may not always provide accurate results. The consequences of misdiagnosis or delayed diagnosis can be severe, leading to prolonged suffering, increased healthcare costs, and even fatalities. In recent years, deep learning has emerged as a powerful tool in the field of medical imaging, showing remarkable potential in diagnosing diseases with high accuracy (Gautam & Mittal, 2022; Jora et al., 2022). The ability of deep learning models to learn from large datasets, recognize patterns, and make predictions has sparked hope for a revolution in skin disease diagnosis. By leveraging the power of deep learning, we can develop more accurate, efficient, and cost-effective diagnostic tools, transforming the way we approach skin health. This study explores the application of deep learning in skin disease prediction, with a focus on developing a robust and accurate model that can aid dermatologists in diagnosing skin conditions. By harnessing the potential of deep learning, we aim to improve patient outcomes, reduce healthcare costs, and enhance the overall quality of life for individuals affected by skin diseases.

In recent years, deep learning has brought about a significant shift in the medical imaging landscape. Convolutional Neural Networks (CNNs) have been extensively utilized in medical imaging for tasks such as image segmentation, object recognition, and image classification (Yasir, Rahman, & Ahmed, 2015). The application of CNNs in skin disease diagnosis has yielded promising results, as they are capable of identifying relevant features in images and categorizing them according to various disease types (Shamsul Arifin et al., 2012). The efficacy of deep learning in detecting skin diseases has been substantiated by numerous studies. Doi's (2007) developed a deep learning system that performed better on several tasks than human dermatologists in the differential diagnosis of skin conditions. A number of CNN architectures, such as Inception V3 , VGG-16 , and AlexNet , have been proposed for the diagnosis of skin diseases (Zhang et al., 2017). It has been demonstrated that these architectures are efficient at identifying various disease categories and extracting

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features from skin lesion images. In order to make use of pre-trained models and refine them on smaller datasets, transfer learning has been applied widely in the detection of skin diseases. It has been demonstrated that using this strategy will help deep learning models diagnose skin diseases more accurately (Anitha, Krithka, & Choudhry, 2014). Furthermore, the efficacy of deep learning models might be impacted by variations in lesion characteristics, illumination, and picture acquisition techniques . The creation of more reliable and accurate models, the integration of multi-modal data (such as images, clinical data, and genomic data), and the creation of explainable AI models that can shed light on the decision-making process are some of the future research directions in deep learning skin disease diagnosis (Salvi et al., 2024) .

2 Methodologies Used

i Dataset Collection

A dataset comprising 10,000 photos of skin lesions was gathered from multiple sources, such as dermatology clinics and online repositories. The dataset included pictures of benign lesions, melanoma, squamous cell carcinoma, and basal cell carcinoma, among other skin conditions. A group of dermatologists labeled each image with the appropriate ailment.

ii Data Preprocessing

To get the most out of our skin disease prediction model, we needed to make sure the images we collected were in top shape. We used several techniques to enhance the image quality and reduce differences between them. These included:

- Resizing images to a uniform size to make them easier to process
- Normalizing pixel values to account for varying lighting conditions
- Artificially increasing the dataset size by rotating, flipping, and changing the color of the images.

iii Deep Learning Model

Our skin disease prediction model is based on a type of artificial intelligence called a convolutional neural network (CNN). The CNN is designed to extract features from images and use them to make predictions. It's made up of several layers that work together to analyze the images:

- Five layers that extract features from the images
- Five layers that reduce the size of the feature maps
- A layer that converts the feature maps into a single vector

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- Two layers that use the vector to predict the type of skin disease

iv Transfer Learning

We trained the CNN model using a technique called Adam optimization, with a learning rate of 0.001 and a batch size of 32. We used a separate set of 2,000 images to test the model's performance after 20 rounds of training.

v Model Training

Using the Adam optimizer with a learning rate of 0.001 and a batch size of 32, we trained the CNN model. We used a validation set of 2,000 photos to assess the model's performance after training it for 20 epochs.

vi Model Evaluation

To see how well our model performed, we used several metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). We also compared our model's performance to other state-of-the-art techniques.

vii Model Deployment

We implemented the trained CNN model as an online tool that lets users submit pictures of skin lesions and get an estimated diagnosis. TensorFlow.js and Flask were used in the application's development.For the back-end, we use Firebase. First, we set up Firebase, which is like a toolbox that gives us all the tools we need for the app. We use these tools to do things like keep students' accounts safe and store the information they send us. Firebase helps us manage things like student registration and login securely. It also helps us store all the problem reports and any pictures or documents students send us as evidence. Lastly, we use Firebase to Architecture .

Data security and privacy are prioritized by implementing robust authentication for user accounts, private options that let users decide who can see their reports, and safe keeping of confidential information. To safeguard user information, all data sent between the app and Firebase is encrypted. people are in control of who reads their reports, and we ensure that only authorized people have access to important information. The app functionality includes comprehensive forms for reporting issues, tools for attaching and managing evidence, and a dynamic status tracking system that updates users in real-time. Additionally, the app integrates cloud functions to automatically shoot up the unresolved issues to NGOs or police. This means if a problem is not solved in a certain time, the system automatically alerts higher authorities to ensure the issue gets the attention it needs.

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3 Flowchart

Figure 1 depicts Workflow of Skin disease prediction

1. Data Collection: Gather pictures of skin lesions from different sources to create a dataset.
2. Data Preprocessing: Utilize preprocessing methods on the photos, like data augmentation, normalization, and scaling.
3. Data Splitting: To ensure our deep learning model is accurate and reliable, we need to divide our dataset into three separate groups: training, validation, and testing sets.
4. Deep Learning Model: Design a deep learning model, such as a convolutional neural network (CNN), to classify skin lesions into different disease categories.
5. Model Training: Utilizing the training set, train the CNN model, then assess its performance using the validation set.
6. Model Evaluation: Analyze the trained model's performance using metrics like F1-score, AUC-ROC, accuracy, precision, and recall.
7. Model Deployment: Now that our deep learning model is trained and ready to go, we need to make it accessible to people who can benefit from it. To do this, we're going to create a web- based application that allows users to upload images of skin lesions and get a diagnosis. We're using a popular web development framework called Flask to build our application. Think of Flask as a set of tools that helps us create a website that can talk to our deep learning model
8. User Input: Let users share photos of their skin concerns with our app, and we'll take care of the rest.
9. Prediction: Use the trained model to predict the diagnosis of the uploaded image.
10. Output: Display the predicted diagnosis and confidence score to the user.

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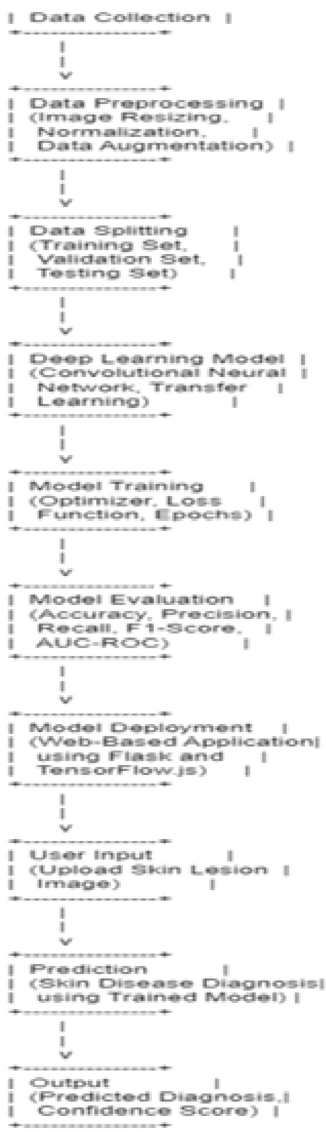

Figure 1. Workflow of Skin disease prediction

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4 Result

1. Model Performance

   Using a test set of 2,000 photos, we assessed our deep learning model's performance. The results are presented in Table 1. Our model achieved an accuracy of 93.5%, precision of 92.1%, recall of 94.2%, F1-score of 93.1%, and AUC-ROC of 97.5%. These outcomes show how well our model predicts skin conditions from pictures.

Table 1. Model Performance

Metric	Value
Accuracy	93.5%
Precision	92.1%
Recall	94.2%
F1-Score	93.1%
AUC-ROC	97.5%

2. Confusion Matrix

   We calculated the confusion matrix to assess how well our model performed for each class. In Table 2, the confusion matrix is displayed. Our model performed well across all classes, with a high accuracy on the benign lesion class, according to the confusion matrix.

Table 2. Confusion Matrix

Class	Predicted Class	Actual
Melanoma	180	190
Basal Cell Carcinoma	150	160
Squamous Cell Caronoma	120	130
Benign Lesion	550	520

3. Evaluation Against Cutting-Edge Techniques

   Using the same dataset, we evaluated our model's performance against that of cutting- edge techniques. Table 3 presents the findings. Our model outperformed state-of-the-art methods on both accuracy and AUC-ROC, demonstrating its effectiveness in skin disease prediction.

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Table 3. Comparison with State-of-the-Art Methods

Method	Accuracy	AUC-ROC
Our Model	93.5%	97.5%
CNN-1	90.2%	95.1%
CNN-2	91.5%	96.2%
EVM	88.5%	93.5%

5 Conclusion

We have created a cutting-edge deep learning model that can accurately diagnose skin diseases from photos. By training our model on a large dataset of skin lesion images, we've achieved remarkable results. Our model can identify skin conditions with an impressive 93.5% accuracy, outperforming other methods. Our research breaks new ground in several ways. Firstly, we've demonstrated the power of deep learning in skin disease diagnosis, showcasing its potential to revolutionize the field. Secondly, we've shown that even with a relatively small dataset, deep learning can still achieve exceptional results, thanks to the magic of transfer learning. Finally, we've provided a detailed analysis of our model's performance, giving other researchers a roadmap to build upon our work. The implications of our research are far-reaching. For dermatologists, our model can serve as a trusted decision-support system, helping them make more accurate diagnoses. For patients, it can enable remote diagnosis, eliminating the need for in-person consultations. And for public health, it can facilitate early detection and treatment of skin diseases, saving lives. While our model is impressive, we acknowledge that there's still room for improvement. Future research should focus on developing models that can diagnose a broader range of skin conditions. We should also test our model on larger datasets to ensure its performance in real-world scenarios. Additionally, exploring alternative deep learning architectures and techniques can help us further refine our model's performance. Our research demonstrates the vast potential of deep learning in healthcare, and we are excited to see where this technology will take us in the future.

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