

Skin Disease Prediction and Classification from Dermoscopy Images Using Neural Network

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Abstract

Skin diseases are among the most common health-related problems affecting people of all age groups, and their occurrence often varies with seasonal and environmental conditions. Delayed or incorrect diagnosis of skin disorders can lead to severe complications, making early and accurate detection extremely important for effective treatment and prevention. In recent years, rapid advancements in deep learning and neural network technologies have significantly contributed to the development of automated medical image analysis systems with improved accuracy and reliability. This study presents a comparative analysis of neural network-based approaches for the prediction and classification of five common skin diseases, namely herpes, melanoma, measles, monkeypox, and chickenpox. The proposed system employs deep neural network models to automatically extract meaningful features from skin lesion image datasets and classify them into predefined disease categories. Image preprocessing and feature learning are performed to enhance classification performance and reduce noise. Multiple neural network architectures are evaluated to analyze their effectiveness in terms of accuracy, precision, and prediction capability. Experimental results demonstrate that the developed models achieve high classification accuracy and show strong potential for reliable disease prediction. The findings indicate that neural network-based automated systems can support dermatologists by providing fast, accurate, and consistent diagnostic assistance, thereby improving early detection and reducing manual diagnostic errors. This approach highlights the growing role of artificial intelligence in medical decision support systems.

Keywords: Chickenpox, CNN, deep learning, dermoscopy, medical imaging, neural network, skin disease

INTRODUCTION

Skin diseases are a global health challenge that affects individuals of all age groups. Traditional approaches rely on visual prediction, which is a time-consuming process and less accurate than modern technology. In rural areas, recent technology might not be applied for diagnosis; however, developments in computer technology, such as CNN and deep learning models, have shown remarkable performance in image prediction, detection, and classification. Automated skin disease diagnosis systems make analysis easier, more accurate, faster, and more cost-effective than traditional approaches. This study focuses on developing a neural-network-based classification and prediction system to identify five different skin diseases.

1. *Herpes*: It is a viral infection generally caused by Herpes Simplex Virus (HSV) and is classified into two types: HSV-1 and HSV-2. HSV-1 causes oral herpes and HSV-2 causes genital herpes [1].
2. *Melanoma*: Melanoma is a serious type of skin cancer that can develop from melanocytes, the cells that produce skin pigment (melanin) [2].

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3. *Sarampion*: Measles is a highly contagious viral disease caused by the measles virus [3].
4. *Monkeypox*: It is a viral disease that affects the skin due to the monkeypox virus in the smallpox [4].
5. *Chickenpox*: Generally, chickenpox is a contagious viral infection caused by the varicella-zoster virus, which is common in children and adults [5].

RELATED WORK

Esteva et al. (2017) [6] evaluated one of the most essential studies in medical imaging analysis by demonstrating that CNN can achieve dermatologist-level performance in the field of classification of skin cancer from dermoscopic images. This study marked a turning point in the adoption of deep learning models for diagnosis. The key contribution of this work is the use of bit-by-bit learning to extract features from every image, such as color and texture. This study used CNN models such as ResNet, DenseNet, and EfficientNet for skin disease classification and prediction; however, it has some limitations in the field of datasets, validation, performance, and automated detection and classification. Yu et al. (2016) [7] proposed a deep learning-based CNN approach for skin disease detection and classification using dermoscopy images. These observations applied ResNet-50 models with transfer learning to effectively extract high-level features from these images. This study used dermoscopy datasets such as ISIC; models such as ResNet and DenseNet were used for robust melanoma detection. Harangi (2018) [8] investigated the effectiveness of deep learning CNN models for melanoma detection from dermoscopy images, focusing on DenseNet. This paper describes how neural networks can be applied to ISIC datasets to extract features. This indicates that DenseNet architecture achieves high classification accuracy as compared to traditional CNN models to extract features such as color and texture from images. Iqbal et al. (2021) [9] proposed models for deep learning skin lesion classification using Mask R-CNN for lesion segmentation and pretrained DenseNet for classification, and used lesion region and DenseNet features to classify dermoscopic images into lesion categories. Deep segmentation and deep CNN frameworks are also used for the automated classification of skin lesions. Abbas Q, Ramzan F, and Ghani MU (2021) [10] proposed a deep learning model for the detection of melanoma from dermoscopic images using CNN, where they used ResNet-18 and generated a performance comparative analysis using custom CNN models; the accuracy of the proposed experiment was 97% on dermoscopy image datasets, and they also compared their models with others such as ResNet-50, ResNet-101, and ResNet-152. Recent developments have explored the application of deep learning technology for the automated classification of viral skin diseases using dermoscopy images. In the proposed experiment, Islam et al. (2022) [11] made a significant contribution by applying large-scale clinical skin image datasets having multiple disease images such as chickenpox, monkeypox, smallpox, and cowpox, using CNN-based classification frameworks to classify various diseases using several neural networks such as ResNet, VGGNet, MobileNet, and DenseNet. In recent years of research development, deep learning approaches have been applied in the field of automated detection of dermatological diseases using skin images. Anand et al. (2022) [12] proposed a CNN-based framework for classifying multiple skin diseases using image datasets of real-world conditions. This study uses CNN models, such as ResNet and VGGNet, to extract features from skin images. Recent advancements in deep learning have significantly affected the automated classification of dermatological conditions using skin images. In this study, Mulani et al. (2023) [13] reviewed CNN methods for medical imaging classification, emphasizing CNN, transfer learning, and data preprocessing [14] to compare traditional methods with recent technology. This study focuses on key concepts for detecting and classifying monkeypox. In this study on automated skin lesion classification using deep learning, Hussain et al. (2022) [15] demonstrated CNN-based experiments to detect chickenpox, monkeypox, and measles from skin images [16]. This work exposed multiple transfer-learning-based pretrained deep learning models to extract features from images [17]. Agarwal and Godavarthi (2023) [18] described the application of CNN for automated skin disease classification and, with the help of skin images, examined, selected models, data preprocessing, and augmentation to describe the performance across different disease categories. Sari and Keser (2025) [19] observed deep learning-based models for the classification of skin diseases using skin images and skin cancer [20]. This study combines AlexNet CNN with feature engineering techniques and SVM with 92% accuracy using ISIC 2017 [21]. This paper describes the benefits of deep learning using classical machine learning components to improve accuracy and efficiency.

METHODOLOGY

Dataset Structure

The dataset in Table 1 represents the distribution of medical images used for training and validation in a classification study, which contains five different diseases related to the skin: herpes, melanoma, measles, monkeypox, and chickenpox. These datasets are typically used in machine learning and medical image classification to classify and predict features using models.

The dataset is divided into two main subsets: training and validation. Training is used for learning patterns and features associated with disease, and validation is used to evaluate the model's performance using model parameters.

Training contained approximately 100 samples per disease (herpes, melanoma, measles, monkeypox, and chickenpox); validation included approximately 30 samples per disease (herpes, melanoma, measles, monkeypox, and chickenpox).

ARCHITECTURE OF SYSTEM

Figure 1 shows the overall architecture of our proposed model, which describes skin disease according to the structural classification of dermoscopy images using CNN [22]. First, we must download our datasets from the folder known as the skin dataset; the datasets contain dermoscopy [23] images of different patients. In preprocessing, all the images are converted into the same format to classify the images properly, and to perform preprocessing, we must use OpenCV. Using segmentation, we try to divide the image into a number of parts to easily extract the features of the images and detect the [24] location where the rheumatoid affected area can be easily detected. After applying the CNN model, we attempted to classify all the images [25] with five grades according to the severity level. Using a random X-ray image of the knee, we attempted to predict the severity level in the patient.

Proposed Model

The above architecture (Table 2) represents the CNN model extracting features from raw images using convolution and pooling layers, converting them into feature vectors, and classifying them into five classes, where each class contains one disease. This architecture is used to determine accuracy and medical diagnostics in the form of detecting and predicting diseases.

Table 1. Dataset structure.

Datasets	Herpes	Melanoma	Measles	Monkeypox	Chickenpox
Training	100	100	101	99	100
Validation	30	30	30	31	29

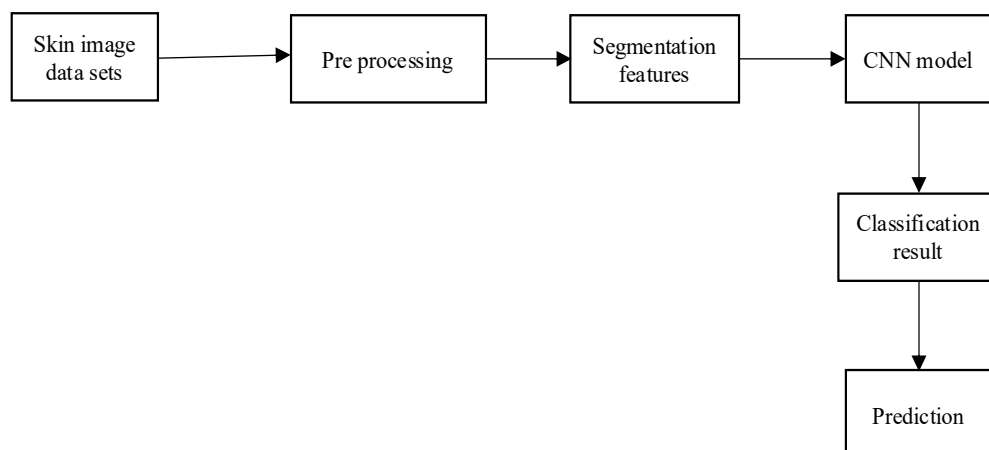


Figure 1. Flowchart of architecture of system.

Table 2. Flowchart of architecture diagram model.

Layer (type)	Output shape	Param #
conv2d (Conv2D)	(None, 126, 126, 16)	160
max_pooling2d (MaxPooling2D)	(None, 63, 63, 16)	0
conv2d_1 (Conv2D)	(None, 61, 61, 32)	4640
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 32)	0
conv2d_2 (Conv2D)	(None, 28, 28, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 64)	0
flatten (Flatten)	(None, 12544)	0
dense (Dense)	(None, 256)	3211520
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 5)	1285
Total params: 3,236,101 Trainable params: 3,236,101 Non-trainable params: 0		

Table 3. Comparative evaluation of various deep learning models.

S.N.	Name of model	Accuracy	Time (second)
1	LeNet	0.8719	164
2	AlexNet	0.7763	351
3	VGGNet	0.6112	3294
4	ResNet	0.8649	408
5	GoogleNet	0.8643	1037
6	MobileNet	0.8903	1209
7	ProposedModel	0.98078	220

EXPERIMENTAL RESULTS

Table 3 presents a comparative evaluation of various deep learning models of classification according to accuracy and computational processing time. Different traditional architectures, such as LeNet and AlexNet, demonstrate moderate performance, achieving accuracies of 0.8719 and 0.7763, respectively. Whereas LeNet has a comparatively low execution time, AlexNet requires high computation time, indicating inefficiency for real-time or large-scale applications in medical imaging.

VGGNet displays the lowest accuracy of (0.6112) and a higher execution time of (3294 seconds), reflecting the deep architecture and large number of parameters, which results in increasing costs without proportional performance in this task.

More advanced architectures, such as ResNet and GoogleNet, achieved accuracies of (0.8649 and 0.8643) with reduced computation as compared to VGGNet, showing the effectiveness of residual connections and inception modules in improving learning efficiency.

The MobileNet model performance has an accuracy of 0.8903 while maintaining a moderate execution time, emphasizing suitability for resource-constrained environments.

Our proposed model achieves the highest accuracy of 0.98078, significantly outperforming all existing models, while requiring 220 s of computation time. This result indicates a balance between the accuracy and computational time, making the proposed method highly effective for practical X-ray image classification and disease prediction tasks.

Ratio Between Validation and Training

Figure 2 illustrates the training and validation accuracy and loss, describing how the models learn over time. The training accuracy increased steadily and reached a high level, whereas the validation accuracy followed a similar trend and stabilized slightly lower, indicating good generalization.

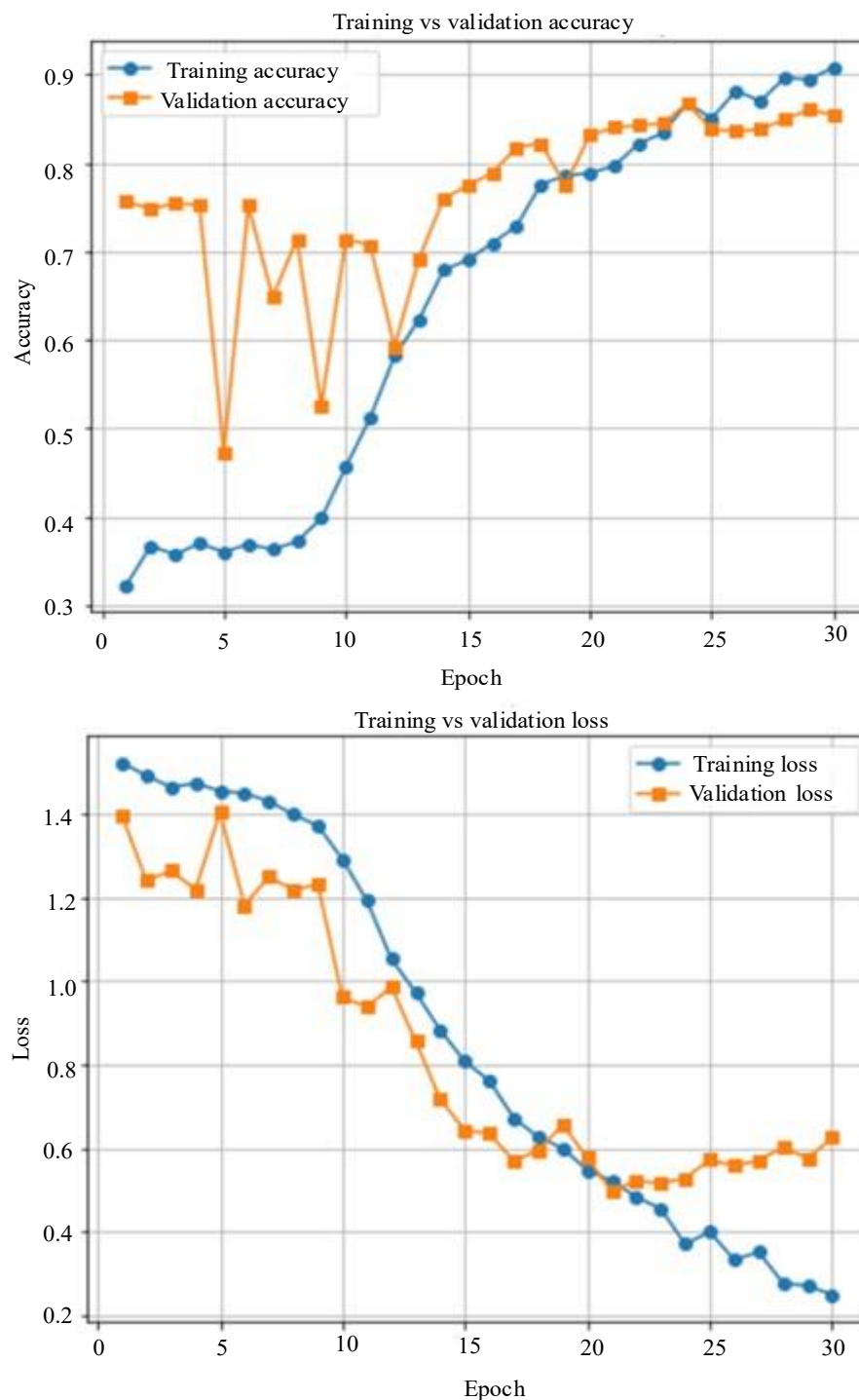


Figure 2. Training and validation accuracy.

Here, both the training and validation losses decrease consistently, confirming that the model minimizes errors. However, a small increase in the validation loss towards the final epochs displays minor overfitting, but it is not significant. Overall, if we analyze the model, it expresses stable learning, excellent performance on unseen data, and reliable convergence for classification and prediction tasks.

CONCLUSION

This study provides a comprehensive overview of neural-network-based approaches for radiological skin image classification and prediction. Deep learning model experiments on strong diagnostic

performance using heterogeneous disease domains. However, the challenges related to data quality, interpretation, and clinical integration in the real world are not excellent. AI research and healthcare professionals must have access to radiological diagnosis.

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