Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 4, 2025

ECZEMA CLASSIFICATION USING MODIFIED CONVOLUTIONAL NEURAL NETWORK RESNET – 50

Duaiy E Amina[1], Ahmad Bilal*[2], Najeeb Ur Rehman Malik[3]

*[*1,2,3]DHA Suffa University, Department of Computer Science Off Khayaban-e-Tufail, Phase VII(Ext), DHA, Karachi.*

DOI:https://doi.org/10.5281/zenodo.15286382

Keywords
Classification, AI, Deep Learning pre-trained models, Convolutional Neural Network, Eczema, VGG, Resnet

Article History
Received on 17 March 2025
Accepted on 17 April 2025
Published on 26 April 2025

Corresponding Author: *
Ahmad Bilal
ahmedbilal60@yahoo.com

Abstract
Skin disorders are serious health issues that impact people of all ages, and many of them still lack a proven treatment. The diagnosis and classification of skin diseases could be greatly enhanced by recent developments in artificial intelligence (AI), especially through deep learning techniques. Early diagnosis made possible by these methods can improve patient outcomes and survival rates. Deep learning models are more effective and possibly more accurate than traditional machine learning techniques since they require less operator involvement for feature extraction. Common inflammatory skin conditions like eczema are typified by dry, itchy, and irritated skin areas. Although the precise etiology of eczema is still unknown, a mix of environmental and genetic factors are thought to be responsible. Convolutional Neural Networks (CNNs) are a specific kind of artificial neural network made to interpret structured grid data, like pictures. It is an essential part of contemporary artificial intelligence (AI) and has transformed a number of domains, including computer vision, by making precise and effective picture processing possible. This study compares many pre-trained deep learning models in terms of improved performance and offers a suggested model method for the classification of eczema conditions. A specially created dataset of eczema photos with two distinct classes—each of which shows how the condition varies from the other—was used to train the machine. Using the suggested methodology, this study successfully classified two forms of eczema with a 97% accuracy rate. In addition to dermatologists and primary care professionals, scientists in the relevant field can utilize this method to reliably classify eczema.

INTRODUCTION

The majority of skin problems have little effect on death rates, while being among the most common diseases. However, skipping or delaying medication can result in a worse quality of life. Skin conditions are regarded as the fourth most common cause of impairment globally, excluding mortality. Skin disorders are a major public health concern and can significantly lower a person's quality of life. The World Health Organization (WHO) estimates that skin issues affect 1.8 billion people globally at any given time, making them a major health concern [1]. The correct and timely diagnosis is crucial for managing skin issues, preventing serious complications, and improving patients' quality of life. In computer science research, the identification of skin diseases has received a lot of interest. The most prevalent chronic skin condition, eczema, affects millions of individuals worldwide. Recently, dermatologists have investigated image processing and artificial intelligence as technical means of autonomously diagnosing skin conditions. The development and evaluation of deep learning models using medical images for the early diagnosis of eczema are thoroughly examined in this thesis.

Classical machine learning algorithms were applied to diagnose skin illnesses in a variety of ways, including the work of [2]. However, [3–7] used a range of Deep Learning methods to classify skin conditions. The diagnosis of eczema has been the focus of only few recent investigations, such as those by [8–11]. Due to their similar looks, it can be challenging to differentiate between different types of eczema. Machine learning is a very time-consuming process when working with big datasets. Deep learning mitigates the problems that standard methods face. It is challenging to increase accuracy in Deep Learning while working with medical imagery. The more photographs there are, the better the machines work.

1. Literature Review

A crucial part of this research project is the literature evaluation, which offers a thorough summary of the body of knowledge on topics like CNN transfer learning, deep learning in medical image analysis, eczema classification methods, and related studies. Around the world, eczema, a chronic skin disease, is a serious health issue. Improving patient outcomes greatly depends on early diagnosis. New developments in machine learning and medical imaging have demonstrated great promise for improving the precision and effectiveness of eczema classification. In order to understand the state of the art in eczema classification, this chapter will examine and summarize the pertinent literature, paying particular attention to deep learning techniques and the application of transfer learning in CNN architectures. We can determine the advantages, restrictions, and areas in need of further research in this sector by looking at earlier studies and methodologies. Our own deep learning model for eczema categorization will be developed and implemented with the knowledge gathered from this literature research. We seek to lay a solid foundation for our research by carrying out an exhaustive literature analysis, making sure that our suggested approach is in line with the state-of-the-art at the moment. Our own deep learning model will be developed and implemented using the recommendations from this review, which will allow us to significantly advance the field of eczema classification. This section describes some earlier research on eczema disorders that used various methods for identifying and categorizing. AL Enezi [31] proposed a skin disease detection method. His method includes image processing technique, and for detection, he used Machine Learning. The dataset was created by collecting images from the internet. The dataset had 100 images of normal skin and three types of skin diseases where 80 images were used for training and 20 images for validation. He extracted features from pre-trained Alex Net model, and then classification was done by using SVM. Three different skin diseases were detected with 100% accuracy. They used an imbalanced dataset in this research, which resulted in over fitting and acquiring an irrelevant accuracy. To categorize skin lesions, Pham et al. [32] used a Deep CNN with Data Augmentation. Images from several sources, such as the ISBI Challenge, ISIC Archive, and PH2 dataset, were combined to produce their dataset. To determine the effect of data augmentation, they used InceptionV4 as the model architecture and assessed its performance using Support Vector Machine (SVM), Random Forest (RF), and Neural Network (NN) classifiers. With an accuracy of 89%, there is yet opportunity for growth. Improving the quality of the dataset may result in increased accuracy. Adegun et al. [33] made a substantial contribution to the study of skin disorders by creating a deep convolutional neural network-based system for separating melanoma from non-melanoma lesions. In a similar vein, Srivastava et al. [34] suggested a segmentation algorithm that uses image processing methods to identify skin that has eczema. Their algorithm, however, is unable to distinguish between various forms of eczema. A different study [35] uses supervised learning to automatically classify eczema. The input photos were first subjected to segmentation and image preprocessing. They then refined them using a feature selection approach after extracting important aspects including color, size, intensity, and texture. Lastly, a Support Vector Machine (SVM) was used for classification, and the accuracy was 84.43%. In order to detect eczema, Jardeleza et al. [36] used SVM for classification and the gray-level co-occurrence matrix for feature extraction. They used the CIELAB color model and K-means clustering to locate the eczema-affected area after first identifying the skin region using the

YCbCr color model. SVM was then used to classify the retrieved gray-level features, yielding an overall accuracy of 83.33%. In their proposed skin disease detection method, Balaji et al. [37] used a Naïve Bayes classifier for classification and the dynamic graph cut method for segmentation. They obtained a 72.7% diagnosis accuracy rate. A deep learning model was presented by Choudhary et al. [38] for the detection of skin lesions. Their method involved segmenting skin lesions after preprocessing input photos with median filters. The segmented images were then subjected to a variety of handmade feature extraction approaches, such as RGB color models and Discrete Wavelet Transform (DWT). Ultimately, a deep learning model was used for classification, with a maximum accuracy of 84.45%. An attention-based CNN model named "Eff2Net" was presented by Karthik R et al. [39] for the categorization of skin diseases. They optimized the input photos for the deep learning model by preprocessing and augmenting them. They then used Eff2Net, their proprietary deep learning architecture, to achieve an accuracy of 84.70% in the final classification. In order to identify skin affected by eczema, Srivastava et al. [40] created a segmentation system that incorporates image processing techniques. Their algorithm, however, cannot distinguish between different forms of eczema.

2. Methodology

An extensive summary of the model architecture details created for the categorization of skin disease is given in this section. Every model architecture is meticulously crafted to effectively extract and assimilate pertinent information from the input photos, hence facilitating precise differentiation between types of eczema.

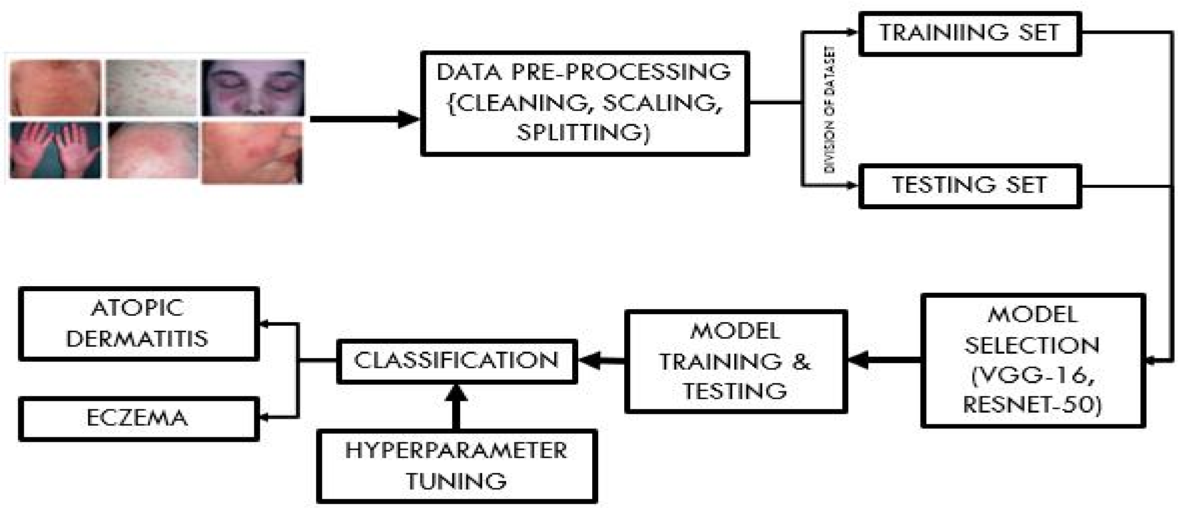

Figure 1: Proposed Methodology

2.1 Dataset Details

We have gather a varied dataset of eczema photos, making sure that the images include a range of eczema types and appearances. We will merge two distinct datasets, from Kaggle, combining 2 types of eczema. DermNet is an open-access dataset comprising approximately 23,000 images, collected and annotated by the DermNet Skin Disease Atlas. It includes diagnoses for 23 primary disease categories, which are further classified into 642 subcategories [30]. However, the dataset contained some duplicate, empty, and irrelevant subcategories. After refining the data, 21,844 images across 622 subcategories were retained. Our dataset is combined from these two datasets available on the internet, Dermnet and Skin Diseases image dataset. Our dataset has two different classes of eczema types.

Figure 2: Dataset Details

2.2 Data Preprocessing

Preprocessing procedures for the gathered dataset will involve picture standardization, and feature enhancement for optimal Eczema classification. The dataset received extensive preprocessing before the models were trained. First, the photos were examined, and any noisy or unnecessary samples were eliminated. The images then underwent resizing and cropping to maintain a standard dimension of 224 by 224 pixels, guaranteeing alignment with the chosen pre-trained models. A variety of data augmentation techniques, such as random zooming, flipping the horizontal and vertical axis, and random rotations, were used to enhance the dataset and increase its diversity.

3. Model Development

A suitable deep learning framework will be used to implement the selected deep learning architectures. The models will be trained on the prepared dataset using methods like transfer learning and performance fine-tuning. The capacity of the trained models to distinguish between eczema and its type will be tested using a variety of performance indicators.

4. Model Architecture

An extensive summary of the architecture details of the models created for the categorization of skin disease Eczema is given in this section. To accurately classify eczema, each model architecture is meticulously crafted to extract and assimilate pertinent elements from the input photos.

5. VGG-16

Simonyan and Zisserman developed the well-known deep convolutional neural network architecture VGG16. It has performed exceptionally well in a range of computer vision tasks. This design, which has 16 weight layers, is highly renowned for its enhanced image classification. Thirteen convolutional layers and three fully linked layers make up VGG16. With a 224x224 pixel fixed input size, the network shows a simple yet very efficient design. Multiple convolutional layers are piled on top of one another in the design, giving the network an increasingly deeper and more complicated structure. VGG16's widespread usage of 3x3 convolutional filters throughout the network is one of its unique features. The network gains proficiency in identifying local and global features found in the input images by employing these tiny filters. This method improves the network's capacity to identify complex linkages and patterns in the data. Owing to its exceptional performance, ease of use, and efficacy, VGG16 has gained popularity in a number of computer vision applications, such as object recognition and image categorization. Its success and widespread adoption in the deep learning field can be attributed to its strong design and powerful feature extraction capabilities.

6. Proposed Model

He et al. created ResNet50, a 50-layer deep neural network design. By adding residual connections, it solves the difficulties associated with training highly dense networks. The network can avoid the vanishing gradient problem and learn residual mappings attributable to these connections. ResNet50 features a 224x224 pixel input size and uses 1x1, 3x3, and 5x5 convolutional filters. It has succeeded in a number of computer vision tasks and has greatly advanced the science of deep learning

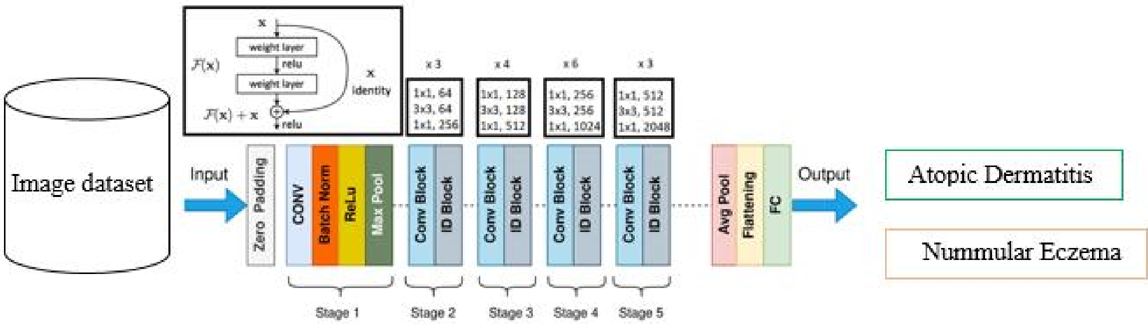

Figure 3: Base Model

The five stages of neural layers that comprise the suggested model are the input layers, convolutional layer (Convo + ReLu), pooling layer, fully connected layer, and output layer. An example of the proposed model architecture was presented. A three-dimensional matrix (Width × Height × Dimension) is sent to the model's input layer. The dimension of the input layer indicates the number of picture channels. For a grayscale image, the dimension is one, and for an RGB image, it is three. A 256 × 256 × 3 input image is sent to the input layer, the model's initial layer. The convolutional layer then receives the input image and applies filters to the original images.

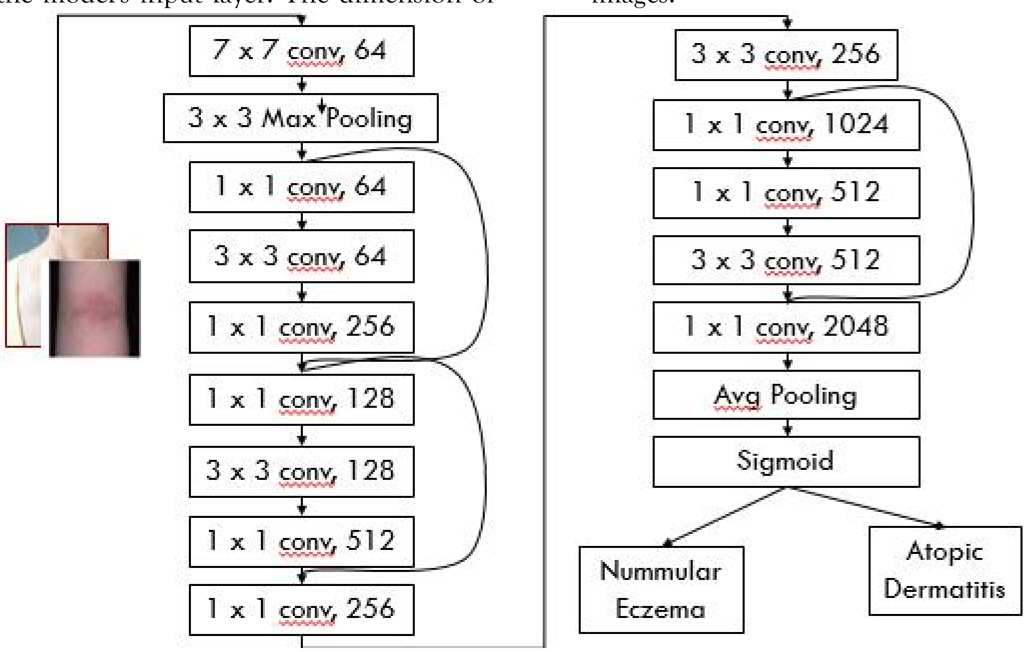

Figure 4: Optimized Layers

7. Model Summary

The table below outlines the configurations used for the Proposed Model.

Parameters	Proposed Model
Input image size	224 x 224
Batch size	64
Learning rate	0.001
Optimizer	Adam
Epochs	15
Loss Function	Categorical crossentropy
Dropout	0.5
Data Augmentation	No
Training/Testing	80%/20%

Table 1: Model Summary

8. Model Implementation

The model is trained using the training set and the fit() algorithm. The training data, the number of epochs, and the batch size are the parameters for this function. During training, the weights of the model are iteratively adjusted in response to the computed loss. After training, the model's performance on the validation set is evaluated using a variety of metrics, such as accuracy, precision, recall, and F1 score. These metrics provide insight into the model's overall effectiveness and ability to correctly categorize the aforementioned illness.

9. Model Evaluation

We thoroughly assess each trained model's performance in this part by taking into account a number of evaluation indicators. These measurements offer important information on how well the models classify skin lesions. The evaluation metrics listed below are frequently used in our research.

a. Accuracy

A key evaluation statistic that gauges how accurate the model's predictions are overall is accuracy. Out of all the samples in the test set, it determines the proportion of correctly identified samples. When it comes to accurately categorizing both types of Eczema, a model with a greater accuracy value is more accurate. Since FP stands for False Positives, FN for False Negatives, TP for True Positives, and TN for True Negatives, the mathematical formula for accuracy is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

b. Precision

A measure called precision assesses the percentage of accurately predicted positive samples among all samples that were projected to be positive. It aids in evaluating the model's resistance to false positives, which occur when an Eczema is mistakenly classified as Atopic Dermatitis. A lower rate of false positives is shown by a greater accuracy score, suggesting that the model produces more dependable positive predictions. The definition of precision in mathematics is:

$$Precision = \frac{TP}{TP + FP}$$

c. F1 Score

The F1 score, a single metric that combines precision and recall, offers a fair evaluation. It provides a comprehensive evaluation of the model's performance and is the harmonic mean of recall and precision. The F1 score is particularly useful when dealing with unbalanced datasets that have significant variances in the number of samples in each class. The following is a mathematical expression for the F1 score:

$$F1\,Score = \frac{2 * (PR)}{P + R}$$

d. Confusion Matrix

A classification model's performance is tabulated in the confusion matrix, which displays the numbers of false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN). It offers a thorough evaluation of the model's predictions, enabling a breakdown of the many kinds of mistakes it has made. The definition of the confusion matrix in mathematics is as follows:

	Predicted Class	
	Positive (P)	Negative (N)
Positive (P)	TP	FN
Negative (N)	FP	TN

Figure 5: Confusion Matrix

10. Graphical Results

It can be inferred from the evaluation metrics and results that Modified Resnet-50 had the best accuracy, demonstrating its greater capacity to distinguish between photos of atopic dermatitis and nummular eczema. Both models, however, have advantages and disadvantages, and the ideal model will ultimately depend on the particular needs and trade-offs that are required for your project. It's critical to take into account the limitations of these findings. The amount and quality of the dataset, the particulars of the implementation, and any presumptions made during the training and assessment phases can all have an impact on the models' performance.

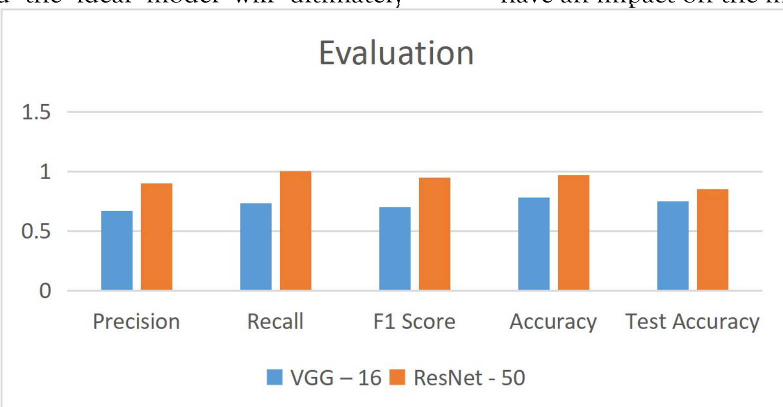

Figure 6: Comparison between two CNN architectures

11. Model Accuracy

The assessment of these models advances the identification of melanoma and offers insightful information about how well they work. Below are the graphs that shows the model's overall accuracy in classifying between the two types of Eczema.

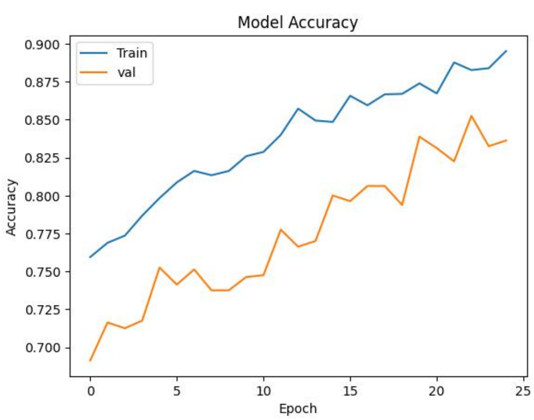

Figure 6(a) VGG- 16 Model Accuracy

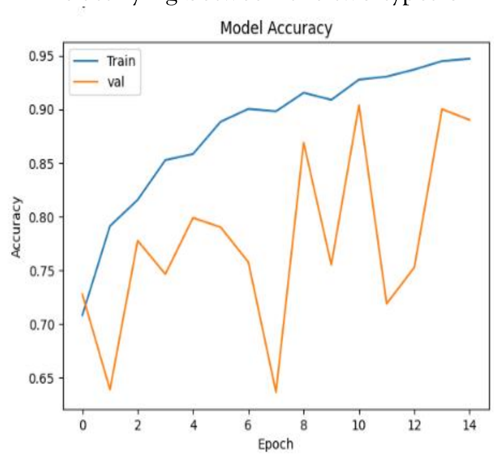

Figure 7(b) Proposed Model Accuracy

12. Conclusion

Despite the fact that the assessed models have demonstrated encouraging outcomes in the identification of Eczema, it is critical to recognize their shortcomings and pinpoint possible areas for development. Among the main restrictions and potential avenues for further study are:

a. Limited data

The amount of the dataset utilized for training and evaluation may have had an impact on the models' performance. The generalization and robustness of the models may be enhanced by a bigger and more varied dataset.

b. Interpretability

Due to their complex architectures, deep learning models are commonly thought of as opaque. Building trust and encouraging the use of these models in clinical settings can be achieved by looking into ways to make them easier to understand and comprehend.

REFERENCES

[1]. Karimkhani *et al.*, “Global Skin Disease Morbidity and Mortality,” *JAMA Dermatology*, vol. 153, no. 5, p. 406, May 2017, doi: https://doi.org/10.1001/jamadermatol.2016.5538.

[2]. Onsoi, J. Chaiyarit, and L. Techasatian, “Common misdiagnoses and prevalence of dermatological disorders at a pediatric tertiary care center,” *Journal of International Medical Research*, vol. 48, no. 2, p. 030006051987349, Sep. 2019, doi: https://doi.org/10.1177/0300060519873490.

[3]. AlKhater, “Accuracy of diagnoses of skin diseases in a pediatric emergency room: A retrospective study,” *Journal of Dermatology and Dermatologic Surgery*, vol. 24, no. 2, p. 116, 2020, doi: https://doi.org/10.4103/jdds.jdds_72_19.

[4]. S. ALKolifi ALEnezi, “A Method Of Skin Disease Detection Using Image Processing And Machine Learning,” *Procedia Computer Science*, vol. 163, pp. 85–92, Jan. 2019, doi: https://doi.org/10.1016/j.procs.2019.12.090.

[5]. Esteva *et al.*, “Dermatologist-level Classification of Skin Cancer with Deep Neural Networks,” *Nature*, vol. 542, no. 7639, pp. 115–118, Jan. 2017, doi: https://doi.org/10.1038/nature21056.

[7]. Li *et al.*, “Artificial intelligence in dermatology,” *Chinese Medical Journal*, vol. 132, no. 17, pp. 2017–2020, Sep. 2019, doi: https://doi.org/10.1097/cm9.0000000000000372.

[8]. Elngar, R. Kumar, A. Hayat, and P. Churi, “Intelligent System for Skin Disease Prediction using Machine Learning,” *Journal of Physics: Conference Series*, vol. 1998, no. 1, p. 012037, Aug. 2021, doi: https://doi.org/10.1088/1742-6596/1998/1/012037.

[9]. Son *et al.*, “AI-based localization and classification of skin disease with erythema,” *Scientific Reports*, vol. 11, no. 1, p. 5350, Mar. 2021, doi: https://doi.org/10.1038/s41598-021-84593-z.

[10]. Rashid *et al.*, “Skin Cancer Disease Detection Using Transfer Learning Technique,” *Applied Sciences*, vol. 12, no. 11, p. 5714, Jun. 2022, doi: https://doi.org/10.3390/app12115714.

[11]. Li *et al.*, “Construction of an artificial intelligence system in dermatology: effectiveness and consideration of Chinese Skin Image Database (CSID),” *Intelligent medicine*, vol. 1, no. 2, pp. 56–60, Aug. 2021, doi: https://doi.org/10.1016/j.imed.2021.04.003.

[12]. Hatem, “Skin lesion classification system using a K-nearest neighbor algorithm,” *Visual Computing for Industry, Biomedicine, and Art*, vol. 5, no. 1, Mar. 2022, doi: https://doi.org/10.1186/s42492-022-00103-6.

[13]. Wang, H. Xia, and Z. Wang, “The Research of Ear Identification Based On Improved Algorithm of Moment Invariant,” pp. 58–60, Jun. 2010, doi: https://doi.org/10.1109/icic.2010.21.

[14]. ALKolifi ALEnezi, “A Method Of Skin Disease Detection Using Image Processing And Machine Learning,” *Procedia Computer*

Science, vol. 163, pp. 85–92, Jan. 2019, doi: https://doi.org/10.1016/j.procs.2019.12.090.

[15]. Pham, C.-M. Luong, M. Visani, and V.-D. Hoang, "Deep CNN and Data Augmentation for Skin Lesion Classification," *Intelligent Information and Database Systems*, pp. 573–582, 2018, doi: https://doi.org/10.1007/978-3-319-75420-8_54.

[16]. `S. Kaymak, P. Esmaili, and A. Serener, "Deep Learning for Two-Step Classification of Malignant Pigmented Skin Lesions," *IEEE Xplore*, Nov. 01, 2018. https://ieeexplore.ieee.org/document/8587019 (accessed Apr. 25, 2022).

[17]. Adegun and S. Viriri, "Deep Learning-Based System for Automatic Melanoma Detection," *IEEE Access*, vol. 8, pp. 7160–7172, 2020, doi: https://doi.org/10.1109/access.2019.2962812

[18]. Adjobo, S. Mahama, P. Gouton, and J. Tossa, "Proposition of Convolutional Neural Network Based System for Skin Cancer Detection," vol. 27, pp. 35–39, Nov. 2019, doi: https://doi.org/10.1109/sitis.2019.00018.

[19]. Sultana and M. B. Uddin, "Multi-Class Skin Cancer Classification Using Modified MobileNet Architecture," pp. 1–5, Apr. 2024, doi: https://doi.org/10.1109/icaeee62219.2024.10561830.

[20]. De, R. Paolo, M. B. Torres, S. Philippe, and M. O. Cordel, "Design and Evaluation of a Multi-model, Multi-level Artificial Neural Network for Eczema Skin Lesion Detection," Dec. 2015, doi: https://doi.org/10.1109/aims.2015.17.

[21]. Alam, T. T. K. Munia, K. Tavakolian, F. Vasefi, N. MacKinnon, and R. Fazel-Rezai, "Automatic detection and severity measurement of eczema using image processing," *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, vol. 2016, pp. 1365–1368, Aug. 2016, doi: https://doi.org/10.1109/EMBC.2016.7590961.

[22]. S. Srivastava, A. Singh, and R. Gupta, "Automatic Detection of Eczema Using Image Processing," *Lecture notes on data engineering and communications technologies*, pp. 171–179, Jan. 2018, doi: https://doi.org/10.1007/978-3-319-75626-4_13.

[23]. Yash Kumar Arora, A. Tandon, and Rahul Nijhawan, "Hybrid Computational Intelligence Technique: Eczema Detection," Oct. 2019, doi: https://doi.org/10.1109/tencon.2019.8929578.

[24]. M. S. Junayed, A. N. M. Sakib, N. Anjum, M. B. Islam, and A. A. Jeny, "EczemaNet: A Deep CNN-based Eczema Diseases Classification," *IEEE Xplore*, Dec. 01, 2020. https://ieeexplore.ieee.org/abstract/document/9334929 (accessed Jan. 11, 2023).

[25]. D. D. Patil and S. G. Deore, "Medical image segmentation: a review," International Journal of Computer Science and Mobile Computing, vol. 2, no. 1, pp. 22–27, 2013.

[26]. L. Cai, J. Gao, and D. Zhao, "A review of the application of deep learning in medical image classification and segmentation," *Annals of Translational Medicine*, vol. 8, no. 11, pp. 713–713, Jun. 2020, doi: https://doi.org/10.21037/atm.2020.02.44.

[27]. K. Zaman and S. S. Maghdid, "Medical images classification for skin cancer using convolutional neural network algorithms," Advances in Mechanics, vol. 9, no. 3, pp. 526–541, 2021.

[28]. K. Zaman, J. I. Bangash, Sozan Sulaiman Maghdid, S. Hassan, H. Afridi, and Muhammad Zohaib, "Analysis and Classification of Skin Cancer Images using Convolutional Neural Network Approach," *2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, pp. 1–8, Oct. 2020, doi: https://doi.org/10.1109/ismsit50672.2020.9255356.

[29]. Gogul and V. S. Kumar, "Flower species recognition system using convolution neural networks and transfer learning," *2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN)*, Mar. 2017, doi: https://doi.org/10.1109/icscn.2017.8085675.

[30]. K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *arXiv.org*, Apr. 10, 2015. https://arxiv.org/abs/1409.1556

[31]. M. N. Bajwa *et al.*, "Computer-Aided Diagnosis of Skin Diseases Using Deep Neural Networks," *Applied Sciences*, vol. 10, no. 7, p. 2488, Apr. 2020, doi: https://doi.org/10.3390/app10072488.

[32]. N. S. ALKolifi ALEnezi, "A Method Of Skin Disease Detection Using Image Processing And Machine Learning," *Procedia Computer Science*, vol. 163, pp. 85–92, Jan. 2019, doi: https://doi.org/10.1016/j.procs.2019.12.090.

[33]. T.-C. Pham, C.-M. Luong, M. Visani, and V.-D. Hoang, "Deep CNN and Data Augmentation for Skin Lesion Classification," *Intelligent Information and Database Systems*, pp. 573–582, 2018, doi: https://doi.org/10.1007/978-3-319-75420-8_54.

[34]. A. A. Adegun and S. Viriri, "Deep Learning-Based System for Automatic Melanoma Detection," *IEEE Access*, vol. 8, pp. 7160–7172, 2020, doi: https://doi.org/10.1109/access.2019.2962812

[35]. S. Srivastava, A. Singh, and R. Gupta, "Automatic Detection of Eczema Using Image Processing," *Lecture notes on data engineering and communications technologies*, pp. 171–179, Jan. 2018, doi: https://doi.org/10.1007/978-3-319-75626-4_13.

[36]. H. Nisar, Yau Kwang Ch'ng, and Yeap Kim Ho, "Automatic Segmentation And Classification Of Eczema Skin Lesions Using Supervised Learning," Nov. 2020, doi: https://doi.org/10.1109/icos50156.2020.9293657.

[37]. S. Gabrielle, J. C. Jose, J. F. Villaverde, and M. Ann, "Detection of Common Types of Eczema Using Gray Level Co-occurrence Matrix and Support Vector Machine," Mar. 2023, doi: https://doi.org/10.1109/iccae56788.2023.10111261.

[38]. V. R. Balaji, S. T. Suganthi, R. Rajadevi, V. Krishna Kumar, B. Saravana Balaji, and S. Pandiyan, "Skin disease detection and segmentation using dynamic graph cut algorithm and classification through Naive Bayes classifier," *Measurement*, vol. 163, p. 107922, Oct. 2020, doi: https://doi.org/10.1016/j.measurement.2020.107922.

[39]. P. Choudhary, J. Singhai, and J. S. Yadav, "Skin lesion detection based on deep neural networks," *Chemometrics and Intelligent Laboratory Systems*, vol. 230, p. 104659, Nov. 2022, doi: https://doi.org/10.1016/j.chemolab.2022.104659.

[40]. R. Karthik, T. S. Vaichole, S. K. Kulkarni, O. Yadav, and F. Khan, "Eff2Net: An efficient channel attention-based convolutional neural network for skin disease classification," *Biomedical Signal Processing and Control*, vol. 73, p. 103406, Mar. 2022, doi: https://doi.org/10.1016/j.bspc.2021.103406.

[41]. S. Srivastava, A. Singh, and R. Gupta, "Automatic Detection of Eczema Using Image Processing," *Lecture notes on data engineering and communications technologies*, pp. 171–179, Jan. 2018, doi: https://doi.org/10.1007/978-3-319-75626-4_13.

[42]. H. Nisar, Yau Kwang Ch'ng, and Yeap Kim Ho, "Automatic Segmentation And Classification Of Eczema Skin Lesions Using Supervised Learning," Nov. 2020, doi: https://doi.org/10.1109/icos50156.2020.9293657.

[43]. M. S. Junayed, A. N. M. Sakib, N. Anjum, M. B. Islam, and A. A. Jeny, "EczemaNet: A Deep CNN-based Eczema Diseases Classification," *IEEE Xplore*, Dec. 01, 2020. https://ieeexplore.ieee.org/abstract/document/9334929

[44]. A. L. Bosma *et al.*, "Classifying atopic dermatitis: a systematic review of phenotypes and associated characteristics," *Journal of the European Academy of Dermatology and Venereology*, vol. 36, no. 6, pp. 807–819, Feb. 2022, doi: https://doi.org/10.1111/jdv.18008.

[45]. Kiki Purnama Juwairi, Dhomas Hatta Fudholi, Aridhanyati Arifin, and Izzati Muhimmah, "An EfficientNet-based mobile model for classifying eczema and acne," *AIP conference*

proceedings, Jan. 2023, doi: https://doi.org/10.1063/5.0118157.
[46]. S. Gabrielle, J. C. Jose, J. F. Villaverde, and M. Ann, "Detection of Common Types of Eczema Using Gray Level Co-occurrence Matrix and Support Vector Machine," Mar. 2023, doi: https://doi.org/10.1109/iccae56788.2023.10111261.
[47]. J. Liu, J. Yan, J. Chen, G. Sun, and W. Luo, "Classification of Vitiligo Based on Convolutional Neural Network," *Lecture notes in computer science*, pp. 214–223, Jan. 2019, doi: https://doi.org/10.1007/978-3-030-24265-7_19.
[48]. T. Agner *et al.*, "Classification of hand eczema," *Journal of the European Academy of Dermatology and Venereology*, vol. 29, no. 12, pp. 2417–2422, Sep. 2015, doi: https://doi.org/10.1111/jdv.13308.
[49]. M. A. Alhamdani and A. Noori Hashim, "Classification of psoriasis and eczema based on Convolutional Neural Network," *IEEE Xplore*, Sep. 01, 2022. https://ieeexplore.ieee.org/abstract/document/10010461?casa_token=lGUuRl_wigAAAAA:r-hq71H9iFEHSsJFMch7S-36zMsI48GfgKde4lXkZT0a4Okd5lk_kZ3qGcHT2r9fpWaXnao (accessed May 08, 2023).
[50]. A. Shrestha and A. Mahmood, "Review of Deep Learning Algorithms and Architectures," *IEEE Access*, vol. 7, pp. 53040–53065, 2019, doi: https://doi.org/10.1109/access.2019.2912200.