.

Deep Learning Techniques for Skin Diseases Classification Using CNN

Asmaa Saleem Zamil[*1] & Asst. Prof. Dr. Hasan Abdulkader[2]
[1,2]Altinbas University/Electrical and Computer Engineering

Abstract:
diagnosing and classifying skin diseases using the eye or clinical examination was not easy, especially the classification of skin cancer diseases. The check process can take a long time and a lot of effort to diagnose the type of disease. Therefore, many algorithms of different performances appeared using Artificial intelligence and techniques for deep learning, which have an effective and significant role in the ability to detect and diagnose, as these techniques are available to be used in all fields, especially in the classification of medical images that show skin diseases. Thus, the primary goal of the study is to continue to discover the models whose role is to find a solution to the classification problem. The proposed model successfully classified nine different classes of skin diseases by using CNN and threshold-Otsu segmentation method,the model's success classification accuracy was 85.8%. The proposed model can find images that don't fit into any of the nine classes. These images are called "unknown images."

Keywords: CNN, segmentation, Deep Learning, skin diseases, Threshold.
DOI: 10.24297/j.cims.2023.1.3

1. Introduction

The epidermis and the dermis are the outermost layers of the skin, while the subcutaneous tissues, blood vessels, lymphatic vessels, nerves, and muscles make up the deeper layers. Protecting the lipids in the epidermis from the damaging effects of moisture leads to an improvement in the barrier function of the skin. Fungal overgrowth, bacteria that go unnoticed, allergic reactions, microbial changes in skin texture, and microbial production of pigment are all potential causes of skin problems [1]. Sometimes, chronic skin diseases progress to malignant tissues. To prevent the worsening of a skin problem, prompt medical attention is required. [2]. Computer-aided diagnosis and detection systems for the early detection of deadly cancerous skin diseases , machine learning techniques' recent applications to computer vision have led to significant advancements in the field.[3]. Many skin conditions include symptoms that can be difficult to treat since they develop for months before a diagnosis is made in such patients. According to a paucity Information and Data a reliance on standardized tasks, Dermoscopy is the term for skin surface microscopy used to examine the skin. Using a computer to make a diagnosis, it is possible to accurately and consistently classify skin conditions to treat patients based on their symptoms [4]. Improving clinical care will be possible because of the accurate classification of diseases. Deep learning models can tackle complex issues by automatically detecting the features of the input data, and they are flexible enough to change as a difficulty under consideration does. Even with minimal Using computer models, such as deep learning models, inferred data can be acquired to uncover and study hidden patterns in otherwise unseen data, yielding a significant amount of efficiency. This inspired the authors to try classifying using a deep learning model the type of skin condition from an image of the affected area[5]. The annual incidence rate of melanoma has increased by 53% over the last decade, from 2008 to 2018, in part because of increased UV exposure. Despite being one of the malignant melanoma, the deadliest kind of skin cancer has a very high probability of survival if it is detected quickly[6]. The classification of skin disease has recently come under the attention of the machine learning community. Automated lesion classification, which can be implemented via apps on mobile devices, can facilitate clinicians' day-to-day work and provide affordable, quick access to life-saving diagnosis beyond hospital walls. [7]. Prior to 2016, four classic machine learning methods had widespread use: preprocessing, segmentation, feature extraction, and classification. [8]. However, it takes a lot of work and application-specific expertise, especially for feature extraction, to determine which traits are important. Early processing failures and data loss also have a substantial impact on classification quality. For instance,low classification accuracy is typically the result of bad feature extraction, which in turn stems from poor segmentation.[9]. Several automated technologies are employed to identify and classify skin disorders. Unlike the vast majority of diagnostic procedures, epidermal identification of these skin diseases does not involve radiological imaging technology. Standard photos can be used to diagnose the condition utilizing Equalization, enhancement, edge detection, and segmentation are all examples of image processing techniques. [10]

2. Related work

Many processed methods for detection and classification approaches have already been reviewed.

A CNN can be used for classification by removing the fully connected layers that were trained on a large dataset. Skin lesions can be categorized with the help of ImageNet. Despite the fact that the features learned are not exclusive to medical images, they are of sufficient quality for lesion categorization.[11].

In the study by Nasr-Esfahani et al. [12], an entirely new two-layer CNN was trained. to tell the difference between benign moles and melanoma based on pictures. There were only 34 photos in the test dataset, and only 136 photos were used to train the model. All of the pictures came from the Department of Dermatology's public picture library at the University Medical Center Groningen. The technique is accurate 81% of the time, only works 80% of the time, and is sensitive 81% of the time. The test data set was very small, so the results should be looked at carefully.

The author in[13]trained and taught to discriminate between six different common skin disorders: vitiligo, eczema, chicken pox, athlete's foot, and skin cancer. This study introduced a key idea for identifying skin diseases utilizing color photographs of diseases using the deep convolutional neural network. The proposed model, when applied to a set of data, produced experimental findings with an accuracy of 81.75%.

The model was defined by Nugroho et al. [14] using a CNN. The model included the three layers that make up CNN: the convolutional layer, the pooling layer, and the fully connected layer. The HAM10000 melanoma dataset was used for this study. The training and testing accuracy of the melanoma detection system are 80% and 78%, respectively.

Kalouche et al.[15]introduced another paper. They classified skin melanoma using ISIC, and they achieved a 78% accuracy rate with a specially trained VGG-16 CNN.Kawahara et al. [16]describe a unique architecture of a CNN ensemble. CNN was separated into many pieces, they looked at the same image, but in various sizes. The results from many resolutions are combined into one final layer. In order to detect interactions at various visual resolutions, end-to-end learning optimizes the weighting parameters of a convolutional neural network (CNN). The Dermot Image Library pictures were used.The system achieves an average categorization accuracy of 79.5%.

Another study using SVM successfully classified 91% of 172 dermatoscopy images into benign and malignant categories. 500 photos from the ISIC archive were used for one of our six categories in this investigation. skin cancer in the form of melanomas [17].

On the one hand, a study used a convolutional neural network to create a system for diagnosing a range of conditions that include actinic keratosis (AK), melanoma, acne, and psoriasis since early detection and diagnosis of skin diseases help with treatment (CNN). Using the Eff2Net model, which correctly classifies disorders into four groups, a rate of 84.70% was obtained[18].

The patient was diagnosed with plaque, punctate, and skin redness after researchers examined psoriasis classification using a combination of Convolutional Neural Network (CNN) and long short-term memory (LSTM) deep learning approaches, and inverse psoriasis. The study found that 125 million people worldwide have psoriasis. It was discovered that deep learning has the potential to be used in various classification tasks where CNN LSTM accuracy reached 84.2% and 72.3%[19].

In this research, we use deep learning techniques to create an automated classification system for skin diseases. To achieve this, digital inputs Noise, lighting effects, hair, and unwanted features are often found in images. So image processing greatly helps CNN in its efforts to speed up the learning process. And identify the distinctive features in the image. Next, the CNN structure is fed with images to classify the inputs. Across disease categories. Dealing based on the constraints of the training dataset and the number of images available. Compared to other classification methods, our experimental results showed greater accuracy. Shown in Table 1.

3. Material and Proposed Method

A. Dataset Description

This study used a dataset of Skin Cancer ISIC consisting of 9 classesthis set consists of 2357 images: a.actinic keratosis ,b.basal cell carcinoma, c.dermatofibroma, d.melanoma, e.nevus, f. pigmented benign keratosis, g. seborrheic keratosis, h. squamous cell carcinoma, I. vascular lesion. The dataset contains images with dimensions 600 *450 pixels. Figure 1 Show Samples of skin diseases.

B. Data splitting

- Training images: - this part contains an 80% mean average (1,872).
- Testing images: - this part contains a 20% mean average (234).

4. Proposed Method

Specifically, this part explains how the suggested approach works. The figure provides an overview of the proposed system. Figure 2, consists of the threshold-Otsu approach for image segmentation and pre-processing stepto remove noise and normalize data. Images that have been preprocessed and sent into a convolutional neural network (CNN) to reduce components that can confound the CNN are processed in this step. Details about these two periods, It is explained as follows:

A. Segmentation

Getting the region of interest is the segmentation step's major goal (ROI).A segmentation framework that used pre-training includes the threshold Otsu algorithm has been proposed. The model was designed using Python for automatic pixel segmentation of dermatology images as shown in figure 3 (a). By separating the diseased area from the healthy region by dividing an image into many homogeneous parts based on the grayscale, texture, color, and image's underlying geometry the region of interest can be obtained using this strategy. A dataset consisting of clinical examples of images showing skin diseases has been used to train the system that has been suggested.

At the beginning of the segmentation method download the images from the dataset, which are 600 * 450 in size, and then convert the image to grayscale And create a mask based on the threshold where it is calculated. The most obvious **T** threshold value is used in the binary mask to identify the "interesting" part of the image that needs to be distinguished. The bounding box identifies and reads the points. The upper left part of the bounding box is (W min, H min) and the lower right corner of the enclosing box is (W max, H max). And then resizing the cropped images of skin disease.

After completing the image segmentation,The threshold approach clusters the image's gray features calculates one or more gray thresholds for the image, then compares the pixel values and threshold magnitudes to assign pixels to the proper categories. Solving the goal function for the ideal threshold is the method's main challenge. Otsu's threshold produces the final image, which is represented by Otsu (x, y).shown in figure 3 (b), the segmentation applied to 1.700 images from (2357) skin diseases images [21].

The segmented image (segment (x, y)) is created by combining Otsu (x, y) with cluster (x, y). This formula is used to derive the segment(x, y) Equation (1). Each pixel has a value in segment(x, y) that is non-zero if and only if its corresponding value in Otsu(x, y) or cluster(x, y) is not zero (x, y).

$$Segment(x,y) = \begin{cases} \mathrm{otsu(x,y)}, & \mathrm{otsu(x,y)} \neq 0 \\ \mathrm{cluster(x,y)}, & \mathrm{cluster(x,y)} \neq 0 \\ 0, \mathrm{otsu(x,y)\ and\ cluster(x,y)} = 0 \end{cases} \quad \textbf{Eq. } \mathit{1}$$

B.CNN Architecture

In this study, a deep learning framework CNN sequentialModel was used for classifying skin disease images. The used CNN in this paper consists of10layers in total, The hyperparameters of the deep neural network were set as follows:the first of which are three convolutional layers the first convolution (128, 5, 5) with the Relu activation functions layer and the second convolution (64, 2, 2) with the Relu activation functions layer and the third convolution (32, 2, 2) with the Relu activation functions layer. Thesecond layerconsists of three pooling layers the first (Is maxPooling2D (pool size=(5, 5) and the second and third pooling layers are (MaxPooling2D (pool size=(2, 2)), and the third was two fully connected layers the first one with Dense layer (128) with the Relu activation functions layer and the second with Dense (7, with the softmax activation functions).and Using compiling optimizer (Adam) to improve random gradient ratios for training deep learning models.

5. Experimental Results

In this part, we evaluate the proposed method on the dataset. That is publicly available for dermatology images [20]. The components of the data set are: 2357images, the proposed system.

Implemented on Python 3.9/64 computer running Windows 10, including a minimum of Intel (R) core i5, 2.30GHz, Ram 8 GB, and 64-bit operating system. . Datasets are randomly divided into test and training sets. A random 80% of the images in the dataset are used for training, while the remaining 20% are used for testing, without any overlapping of the test samples and the train samples. A batch size of 32 is used for the data that is being fed into the network for training purposes.

A.Skin diseases Segmentation Results Analysis

The network has been trained using images. The learning and testing technique is performed for 200 iterations so that results are independent of training and test data selections.

The mean values for several groupings of results are presented.

Regarding the quantitative assessment of performance, the suggested approach measures five regularly employed scales in Classification difficulties. This understanding of metrics is as follows in Table 2.

B. Skin diseases classified result

Figure 4 compares the CNN accuracy and the Convolution neural network's Loss function based on number of epochs by displaying the accuracy graphs concerning the number of epochs. Table 3 displays the loss comparison graphs of various CNN classification techniques.

6. Conclusions

To classify skin diseases, this research used a deep-learning classification approach. To classify 2357 images of common diseases. After extracting the features and properties of color, texture, and shape, a convolutional neural network (CNN) was used. The CNN app provided an accuracy of 85.8%. The achieved accuracy shows that the proposed deep learning application is reliable and efficient. It could lead to the enhancement of medical methods used in the detection of diseases. Where the results of the training showed that the rate was reliable and worked with multiple classifiers, andbetter accuracy values were obtained for categorizes classification.

References

1. M. A. M. Almeida and I. A. X. Santos, "Classification models for skin tumor detection using texture analysis in medical images,"J. Imaging, vol. 6, no. 6, p. 51, 2020.
2. V. Ki and C. Rotstein, "Bacterial skin and soft tissue infections in adults: a review of their epidemiology, pathogenesis, diagnosis, treatment, and site of care," Can. J. Infect. Dis. Med. Microbiol., vol. 19, no. 2, pp. 173–184, 2008.
3. A. Masood and A. Ali Al-Jumaily, "Computer-aided diagnostic support system for skin cancer: a review of techniques and algorithms," Int. J. Biomed. Imaging, vol. 2013, 2013.
4. P. N. Srinivasu, J. G. Sivasai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of skin disease using deep learning neural networks with mobile net v2 and lstm," Sensors, vol. 21, no. 8, pp. 1–27, 2021, doi: 10.3390/s21082852.

5. P. N. Srinivasu, J. G. SivaSai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of skin disease using deep learning neural networks with MobileNet V2 and LSTM,"Sensors, vol. 21, no. 8, p. 2852, 2021.
6. N. Nami, E. Giannini, M. Burroni, M. Fimiani, and P. Rubegni, "Teledermatology: state-of-the-art and future perspectives,"Expert Rev. Dermatol., vol. 7, no. 1, pp. 1–3, 2012.
7. R. E. Foraker et al., "EHR-based visualization tool: adoption rates, satisfaction, and patient outcomes,"eGEMs, vol. 3, no. 2, 2015.
8. G. Fabbrocini et al., "Epiluminescence image processing for melanocytic skin lesion diagnosis based on 7-point check-list: a preliminary discussion on three parameters,"Open Dermatol. J., vol. 4, no. 1, 2010.
9. T. J. Brinker et al., "Skin cancer classification using convolutional neural networks: systematic review,"J. Med. Internet Res., vol. 20, no. 10, p. e11936, 2018.
10. P. Deepalakshmi, K. Lavanya, and P. N. Srinivasu, "Plant leaf disease detection using CNN algorithm,"Int. J. Inf. Syst. Model. Des., vol. 12, no. 1, pp. 1–21, 2021.
11. A. Menegola, M. Fornaciali, R. Pires, F. V. Bittencourt, S. Avila, and E. Valle, "Knowledge transfer for melanoma screening with deep learning," in 2017 IEEE 14th international symposium on biomedical imaging (ISBI 2017), 2017, pp. 297–300.
12. E. Nasr-Esfahani et al., "Melanoma detection by analysis of clinical images using convolutional neural network," in 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2016, pp. 1373–1376.
13. R. Saifan and F. Jubair, "Six skin diseases classification using deep convolutional neural network.,"Int. J. Electr. Comput. Eng., vol. 12, no. 3, 2022.
14. A. A. Nugroho, I. Slamet, and Sugiyanto, "Skins cancer identification system of HAMl0000 skin cancer dataset using convolutional neural network," in AIP Conference Proceedings, 2019, vol. 2202, no. 1, p. 20039.
15. S. Kalouche, A. Ng, and J. Duchi, "Vision-based classification of skin cancer using deep learning,"2015, Conduct. Stanfords Mach. Learn. course (CS 229) taught, 2016.
16. J. Kawahara and G. Hamarneh, "Multi-resolution-tract CNN with hybrid pretrained and skin-lesion trained layers," in International workshop on machine learning in medical imaging, 2016, pp. 164–171.
17. E. Çevik and K. Zengin, "Classification of skin lesions in dermatoscopic images with deep convolution network,"Avrupa Bilim ve Teknol. Derg., pp. 309–318, 2019.
18. 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, "Biomed. Signal Process. Control, vol. 73, p. 103406, 2022.
19. S. F. Aijaz, S. J. Khan, F. Azim, C. S. Shakeel, and U. Hassan, "Deep Learning Application for Effective Classification of Different Types of Psoriasis,"J. Healthc. Eng., vol. 2022, 2022.
20. “skin-cancer9-classesisic @ www.kaggle.com.” [Online]. Available: https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic

21. G. Ma and X. Yue, "An improved whale optimization algorithm based on multilevel threshold image segmentation using the Otsu method,"Eng. Appl. Artif. Intell., vol. 113, p. 104960, 2022.
22. M. H. Jafari, E. Nasr-Esfahani, N. Karimi, S. M. Soroushmehr, S. Samavi, and K. Najarian, "Extraction of skin lesions from non-dermoscopic images for surgical excision of melanoma,"Int. J. Comput. Assist. Radiol. Surg., vol. 12, no. 6, pp. 1021–1030, 2017.

Table 1. summary of studies in related work for skin disease classification

Classifier technique	Categories	Number of images	Accuracy	Reference
CNN	melanoma detection	170	81%	[12]
CNN	skin diseases classification	3000	81.75%	[13]
CNN	Skin cancer identification	10015	78%	[14]
VGG-16	skin melanoma classification	1280	78%	[15]
CNN	skin lesion classification	1300	79.5%.	[16]
SVM	melanoma skin cancer	500	91%	[17]
Eff2Net	skin diseases diagnosis	-	84.70%	[18]
CNN	Classification of Different Types of Psoriasis	1468	84.2%	[19]
LSTM			72.3%	
CNN	**Skin diseases classification**	**2357**	**85.8%**	**Proposed work**

Figure 1. Samples of skin diseases[20].

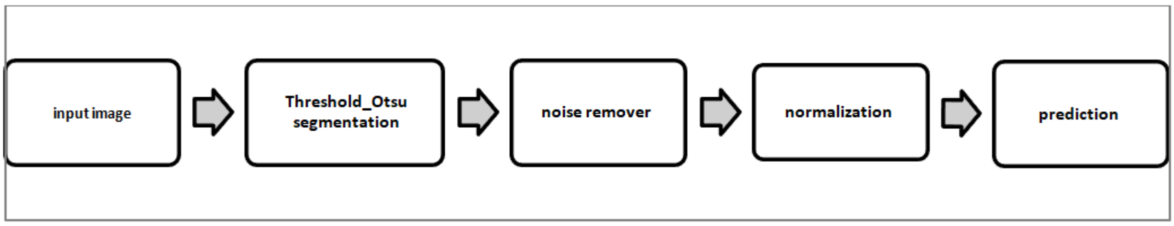


Figure2: proposed method for skin disease classification using CNN model

(a)

(b)

Figure3: Results obtained by applying the Threshold Otsu algorithm

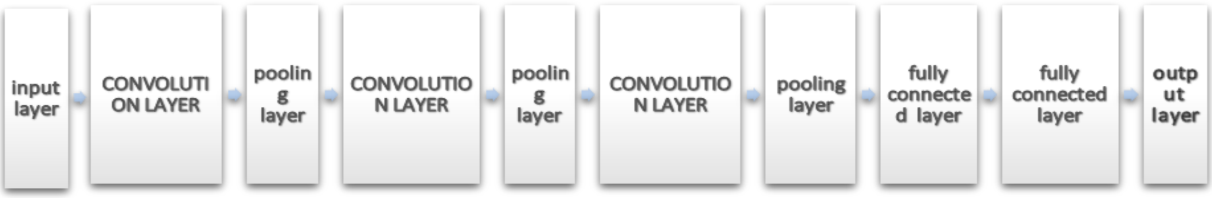


Figure 4: The CNN model for skin disease classification.

Table 2. evaluation metrics [22]

$\text{Accuracy} = \frac{\text{True Corrected Result}}{\text{Total No. Of Result}}$
$\text{F1} - \text{Score} = \frac{2 * (\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$
$\text{Recall} = \frac{\text{True Positive Case}}{\text{True Positive Case} + \text{False Negative Case}}$
$Precision = \frac{True\ positive\ case}{True\ positive\ case + False\ positive\ case}$

Table 3. skin diseases segmentation result

Total image	Segment images	False detection	Error Rate	Accuracy
2357	1,700	265	1.5	85.8%

Table 4. model accuracy and model loss

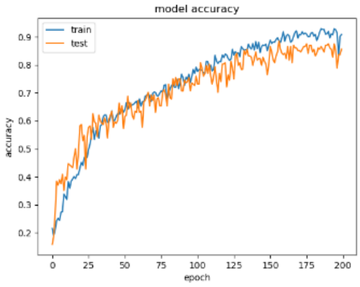
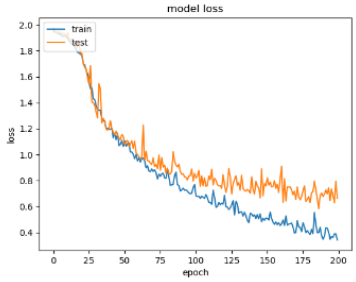
Epoch	Model accuracy	model loss function
200		

Table 5. result with different epochs

Epoch	TRAIN ACCURACY	TRAIN LOSS	TEST ACCURACY	TEST LOSS
60	0.5650	1.0029	0.5862	1.1548
150	0.8974	0.3875	0.9361	0.3921
200	**0.9014**	**0.0254**	**0.8657**	**0.2457**