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M U N D A R I J A
C O N T E N T S

№	Maqola nomi	Article title	Bet/ page
1	Yemirilishni hisobga olgan holda ikki zonali g‘ovak muhitda degradatsiyalanuvchi modda ko‘chishi **Xo‘jayorov B., Fayziev B., Sagdullaev O., Haydarov O.**	Transport of a degrading solute in a two-zone porous medium taking into account the decay **Khuzhayorov B., Fayziev B., Sagdullaev O., Khaydarov O.**	**5-11**
2	Fizik-kimyoviy usullar yordamida kadmiy ionlarini aniqlovchi ion-selektiv elektrod membranasining tuzilishi **Abduraxmanov E., Salimova Sh., Jumanova G.**	Membrane structure of ion-selective electrode for determining cadmium ion, analyzed by physicochemical methods **Abdurakhmanov E., Salimova Sh., Jumanova G.**	**12-17**
3	Tasodifiy qo‘zg‘alishlarda elastik sterjenning chiziqlimas ko‘ndalang tebranishlarini so‘ndirish masalasi **Dusmatov O., Kasimova F.**	Problem of absorber nonlinear transverse vibrations of an elastic rod under random impacts **Dusmatov O., Kasimova F.**	**18-22**
4	Birjinsli tekis-radial muhitda anomal filtratsiya **Xo‘jayorov B., Maxmudov J., Akramov Sh.**	Plane-radial anomalous filtration of liquid in homogeneous porous medium **Khuzhayorov B., Makhmudov J., Akramov Sh.**	**23-28**
5	Parasetamolning molekulyar xususiyatlariga erituvchining ta’siri **Holikulov U., Jumabaev A., Xudaykulov B., Yormatov Sh., Safarov A.**	Solvent effect on the molecular properties of paracetamol **Holikulov U., Jumabaev A., Khudaykulov B., Yormatov Sh., Safarov A.**	**29-35**
6	Tibbiy tasvirlar asosida teri kasalliklarini tasniflashning mashinaviy o‘qitish va chuqur o‘qitish yondashuvlari **Boboxonov A., Xuramov L., Rashidov A.**	Machine learning and deep learning approaches to classify skin diseases based on medical images **Bobokhonov A., Khuramov L., Rashidov A.**	**36-48**
7	Urbanizatsiya jarayonlarini hududiy tashkil etilishida xorijiy davlatlar tajribasi **Ibragimov L., Baratova G.**	The experience of foreign countries in the territorial organization of urbanization processes **Ibragimov L., Baratova G.**	**49-55**
8	Singulyar sirtlar uchun transversallik sharti **Usmanov S.**	Transversality condition for singular surfaces **Usmanov S.**	**56-60**
9	Tuproq namligini o'lchovchi avtonom sensorlar uchun $KPbBr_3$ nanokompoziti **Rahmonova M., Muxamadiev N., Galyamitdinov Y.**	$KPbBr_3$ nanocomposite for autonomous agro soil moisture sensors **Rahmonova M., Mukhamadiev N., Galyamitdinov Y.**	**61-67**
10	Fotoelektrik modul yuzasi ifloslanishi jarayonining matematik modeli **Muminov R., Utamuradova Sh., Dyskin1 V., Tukfatullin O., Butunbaev B.**	Mathematical model of the soiling process of a photovoltaic module surface **Muminov R., Utamuradova Sh., Dyskin1 V., Tukfatullin O., Butunbaev B.**	**68-74**
11	Landshaft komplekslarini tadqiq etishda landshaft-meliorativ yondashish va baholash **Eshquvvatov B., Xurramova N., Saydullayeva S.**	Landscape-ameliorative approach and assessment in the study of landscape complexes **Eshkuvvatov B., Khurramova N., Saydullaeva S.**	**75-80**
12	Yuklangan Hirota tenglamani sochilish nazariyasining teskari masalalari usulida integrallash **Hoitmetov U., Musoyeva F.**	Integrating the loaded Hirota equation via the inverse scattering method **Hoitmetov U., Musoeva F.**	**81-91**
13	Tebranishlardan himoyalanuvchi mexanik sistemaning chiziqlimas tasodifiy parametrik tebranishlari **Dusmatov O., Xodjabekov M., Ashurov B.**	Nonlinear random parametric oscillations of a vibration-proofed mechanical system **Dusmatov O., Xodjabekov M., Ashurov B.**	**92-100**
14	Qisman-izospektral Shturm-Liuvill operatorlari va ularning tatbiqlari **Mirzaev O., Abdunazarov R., Nosirova G.**	Partially-isospectral Sturm-Liouville operators and their applications **Mirzaev O., Abdunazarov R., Nosirova G.**	**101-111**
15	Texnogen omillarning Ohangaron daryo havzasi landshaftlari ifloslanishiga ta'siri **Fozilov A.**	The influence of technogenic factors on the pollution of landscapes of the Akhangaran river basin **Fozilov A.**	**112-116**
16	Trisiklik 7-дезапуринлар синтези **Kuryazov R.Sh., Shonazarov A.R., Zhao J., Bozorov Kh.A.**	Synthesis of tricyclic 7-deazapurines **Kuryazov R.Sh., Shonazarov A.R., Zhao J., Bozorov Kh.A.**	**117-121**
17	Trisiklik pirrolo[2,3-*D*]pirimidin tizimida karbonil-amin kondensatsiyasi orqali iminlar sintezi **Kuryazov R.Sh.**	Synthesis of imines via carbonyl-amine condensation in the tricyclic pyrrolo[2,3-d]pyrimidine system **Kuryazov R.Sh.**	**122-126**

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MACHINE LEARNING AND DEEP LEARNING APPROACHES TO CLASSIFY SKIN DISEASES BASED ON MEDICAL IMAGES

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Abstract. Currently, many studies are being conducted to classify skin diseases at early stages and several solutions are being proposed. In particular, classification of skin diseases using medical images using intelligent systems is one of the best solutions proposed by researchers. In this research work, the methods, models and algorithms proposed by scientists for automatic classification of skin diseases based on computer-aided machine learning (ML) and deep learning (DL) algorithms were analyzed. Also, pre-processing methods for medical images were studied for the fast and accurate operation of ML and DL models. As a result of the analysis, comparative tables of previous and current research results and the models proposed in them were developed for further research work. The main goal of the study is to fill the research gap in the application of ML and DL models in skin disease classification, which will help researchers to find better solutions, to find out the current difficulties in classification and recent achievements.

Keywords: classification, deep learning, image preprocessing, machine learning, medical images, skin diseases, segmentation.

Tibbiy tasvirlar asosida teri kasalliklarini tasniflashning mashinaviy o‘qitish va chuqur o‘qitish yondashuvlari

Annotatsiya. Hozirgi vaqtda teri kasalliklarini dastlabki bosqichlarda aniqlash bo‘yicha ko‘plab tadqiqotlar olib borilmoqda va bir nechta yechimlar taklif qilinmoqda. Xususan, intellektual tizimlar yordamida tibbiy tasvirlar asosida teri kasalliklarini tasniflash tadqiqotchilar tomonidan taklif qilingan eng yaxshi yechimlardan biridir. Ushbu tadqiqot ishida teri kasalliklarini kompyuter yordamida mashinaviy o‘qitish (ML) va chuqur o‘qitish (DL) algoritmlariga asoslangan holda teri kasalliklarini avtomatik tasniflash uchun olimlar tomonidan taklif qilingan usullar, modellar va algoritmlar tahlil qilindi. Shuningdek, ML va DL modellarining tez va aniq ishlashi uchun tibbiy tasvirlarni oldindan qayta ishlash usullari o‘rganildi. Tadqiqot natijasida keyingi tadqiqot ishlari uchun oldingi va joriy tadqiqot natijalarining qiyosiy jadvallari hamda ularda taklif etilgan modellar tahlil qilindi. Tadqiqotning asosiy maqsadi teri kasalliklarini tasniflashda ML va DL modellarini qo‘llash bo‘yicha tadqiqot bo‘shlig‘ini to‘ldirishdir, bu tadqiqotchilarga yaxshiroq yechimlarni topishga, tasniflashdagi mavjud qiyinchiliklarni va so‘nggi yutuqlarni aniqlashga yordam berish.

Kalit so‘zlar: tasniflash, chuqur o‘qitish, tasvirga oldindan ishlov berish, mashinaviy o‘qitish, tibbiy tasvirlar, teri kasalliklari, segmentatsiya.

Подходы машинного обучения и глубокого обучения для классификации кожных заболеваний на основе медицинских изображений

Аннотация. В настоящее время проводится много исследований по классификации кожных заболеваний на ранних стадиях и предлагается несколько решений. В частности, классификация кожных заболеваний с использованием медицинских изображений с использованием интеллектуальных систем является одним из лучших решений, предложенных исследователями. В данной исследовательской работе были проанализированы методы, модели и алгоритмы, предложенные учеными для автоматической классификации кожных заболеваний на основе алгоритмов машинного обучения (ML) и глубокого обучения (DL). Также были изучены методы предварительной обработки медицинских изображений для быстрой и точной работы моделей ML и DL. В результате анализа были разработаны сравнительные таблицы предыдущих и текущих результатов исследований и предложенных в них моделей для дальнейшей исследовательской работы. Основная цель исследования — заполнить пробел в исследованиях в применении моделей ML и DL в классификации кожных заболеваний, что поможет исследователям найти лучшие решения, выяснить текущие трудности в классификации и последние достижения.

Ключевые слова: классификация, глубокое обучение, предварительная обработка изображений, машинное обучение, медицинские изображения, кожные заболевания, сегментация.

I. Introduction. Worldwide, skin diseases account for 1.79% of the global burden of all other types of disease. According to the American Academy of Dermatology, 1 in 4 people in the United States have a skin disease [1]. The most common and dangerous types of skin diseases are eczema, melanoma, psoriasis, squamous cell carcinoma, basal cell carcinoma, etc. [2]. Today, modern intelligent systems have emerged as a promising approach to develop automated and objective computer-based classification models for skin diseases. Accurate classification of skin diseases using automated systems is a very important task. Because it directly affects human life. Therefore, even a small uncertainty can put the lives of patients at risk. Therefore, over the past few decades, researchers have been working on developing methods to automatically diagnose various forms of skin diseases by applying machine learning and deep learning methods and improving their accuracy.

The purpose of this study is to review ML and DL methods that can be used for computer-aided diagnosis of skin diseases, as well as to analyze previous and current studies on the classification of skin diseases. The relevance of the research work is to analyze the methods of correctly selecting artificial intelligence models and adjusting their parameters in the classification of skin diseases, as well as the application of pre-processing techniques to medical images. Since these methods are used to perform initial assessments of the most suspicious skin lesions. The study analyzed the quality of evidence, the usefulness of algorithms, the different types of skin diseases for which artificial intelligence is used, the impact on primary care, and the possibilities of using computers.

The main focus of intelligent systems for detecting skin diseases using skin surface images is to extract the characteristics of these diseases. Knowing the specific characteristics of each disease and its location on the skin surface is a key step in classifying the disease. Table 1 below lists some common skin diseases and their characteristics.

Table 1. Common skin diseases and their characteristics

Skin disease appearance	Type of disease	Characteristics	Location on the body
	Eczema	It is the most common chronic inflammatory skin disease, affecting 15–30% of children and 2–10% of adults worldwide [3]. In people with fair skin, eczema rashes may appear pink, red, or purple. If the skin is darker, the eczema rash may be purple, brown, or gray.	Eczema is most common on the elbows, backs of the knees, neck, and face.
	Psoriasis	It is a common chronic immune-mediated inflammatory skin disease, affecting approximately 2–3% of the general population worldwide [4]. The disease presents as a silvery, red, scaly rash.	It can involve the palms and soles of the human body, the scalp, and the nails. The disease most often manifests itself in a sharply demarcated appearance on the flexural surfaces of the elbows and knees and in the lumbar region [5].
	Lupus Erythematosus	The incidence of lupus is 241 per 100,000 adults in the United States and 210 per 100,000 in Spain [6, 7].	Any part of the body
	Basal Cell Carcinoma (BCC)	Basal cell carcinoma (BCC) can appear on the skin as a flesh-colored, pearly lump or a pinkish spot. It often appears as a shiny, pearly, or clear bump or nodule that is pink, red, or white [8].	It is usually found on the skin of the face, neck, and ear areas.
	Squamous Cell Carcinoma (SCC)	A hard bump on the skin called a nodule. The nodule may be the same color as the skin or may look different. Depending on the skin color, it may appear as a flat sore with a crust that is pink, red, black, or brown [9].	It is usually found on the skin of the face, neck, and ear areas.
	Melanoma	It often develops within the skin or may appear suddenly as a new, dark spot on the skin. The spot is asymmetrical, meaning that the two sides do not match, and the borders of the spot may be uneven or defined. The spot may be of several colors, including brown, black, red, blue, or white [9].	Among men, melanoma usually develops on the upper body, especially the upper back, while among women, melanoma most often appears on the legs.

Analyzing skin diseases based on medical images, it is necessary to extract the specific features of skin diseases. Dermatological diseases, unlike internal diseases, usually manifest externally, therefore, a deep understanding of visual signs and subtle differences in skin texture, color, and pattern is required [10]. Capturing and analyzing these complex visual features is essential to ensure accurate and reliable classification of skin diseases. By applying medical image processing technologies based on ML and DL algorithms, scientists are developing approaches to diagnose skin lesions with complex features. These approaches are expected to lead to better classification of skin diseases, more accurate

diagnosis of patients, and more effective global health care [11]. The organization of this research work is as follows (Figure 1): Section 2 presents a literature review; Section 3 discusses the general methodology of ML and DL approaches in skin disease diagnosis; Section 4 presents the research results; and Section 5 presents the research conclusions.

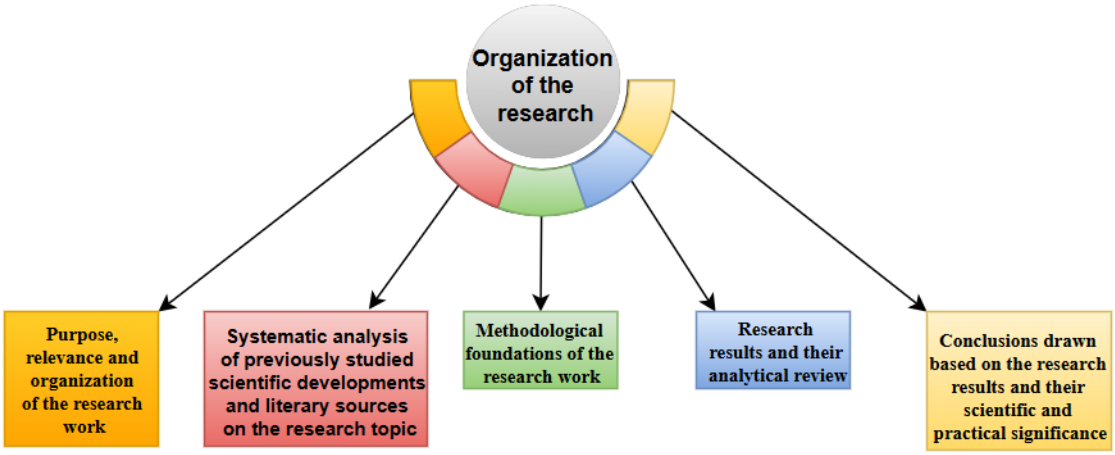


Figure 1. Research organization diagram

II. Literature review. Today, ML and DL have emerged as promising approaches to develop automated and objective classification models for skin diseases using computers. The high accuracy of ML and DL techniques in classifying skin diseases has led to their increased application. This section reviews the studies conducted by researchers in the field of diagnosing some common skin diseases using DL and ML models.

Several studies have proposed the use of ML algorithms for eczema detection. In particular, in the article "A method for automatic eczema disease classification using supervised learning" by researchers Nisar H., Ch'ng Y.K., Ho Y.K., supervised learning ML algorithms for eczema classification using Support Vector Machine (SVM), Naive Bayesian Classifier (NBC) and K-Nearest Neighbor (KNN) algorithms were presented [12]. The researchers initially performed image preprocessing methods on the acquired images to improve image quality and performed image segmentation. The features obtained from the training images were ranked using Fisher score, standard deviation, T-statistic score and correlation coefficient to extract the most important features. In this, the researchers used features such as color, size, intensity and texture to train the model. As a result of the classification, the SVM classifier shows the best segmentation result with an accuracy of 84.43%, while the accuracy of NBC and KNN is 82.77% and 83.53%, respectively.

Researchers such as M. Jagdish, SP Gualan Guamangate, MAG Lopez, JA De La Cruz-Vargas, MER Camacho have conducted research on skin disease classification using ML algorithms [13]. They developed skin disease detection models using image processing techniques. To classify skin diseases, 50 image samples were taken from the skin surface and pre-processed using wavelet analysis. Using the pre-processed sample images for classification, they used fuzzy clustering methods with KNN and SVM ML algorithms. They achieved 91.2% classification accuracy using the KNN classification algorithm. According to the results of the study, when the KNN algorithm was compared with the SVM technique, it was found that the KNN algorithm performed better. Scientists identified the types of skin diseases using these classification methods. However, they only used 50 sample images, which included basal and squamous cell carcinoma diseases.

Using images of skin surfaces affected by diseases such as melanoma, psoriasis, and acne, researchers S.A. AlDera, M.T.B. Othman presented a model for diagnosing skin diseases [14]. The researchers used a dataset of 377 images of 4 different disease classes in this work. During the pre-processing stage, the image samples obtained were resized to 250*250 and the median method was used to reduce noise in the images. Then, the color images were converted to a grayscale model for segmentation and extraction tasks and the Otsu method was used for segmentation. In this work, features were extracted using Entropy, Gabor, and Sobel methods to extract image texture features. Finally, after the features were extracted, a model was developed based on ML algorithms SVM, Random Forest (RF), and K-Nearest Neighbors (KNN) classifiers for disease classification. The results of the proposed

model show that SVM achieved 90.7% accuracy, while RF and KNN achieved 84.2% and 67.1%, respectively. As a result, the SVM classifier achieved better accuracy than other ML algorithms. The model proposed by the researchers can only achieve high accuracy when using a larger dataset of images.

Researcher Mustafa Qais Hatem developed an algorithm to classify skin diseases as dangerous or safe using their lesions [15]. He used a KNN algorithm to classify skin lesions according to their severity. The proposed system used dermoscopic images as a dataset. In the initial stage, morphological "closure" was used to improve image clarity, facilitate skin lesion segmentation, and filter the shape and structure of the image. Both traditional and adaptive thresholding methods were used to segment skin lesions. Then, segmented dermoscopic lesions were used to extract disease features. Lesion parameters were determined using mathematical formulas such as the mean value. The system proposed by the researcher achieved 98% accuracy using a KNN classifier for only two classes (dangerous or safe).

Jonathan Souza, Tiago Mota de Oliveira, Claudemir Casa, and Andre Roberto Ortoncelli [16, 17] researchers conducted a study on the early detection of lupus skin disease from images and proposed an automatic lupus detection approach. The study used 905 lupus images as an experimental database. In the preprocessing stage, all images in the database were resized to a standard size of 224x224 and new images were created to increase the data. This approach combines a clustering strategy and a Transfer Learning-based lupus detection method. The experiments were conducted with eight pretrained models of the CNN architecture, and the highest accuracy of 96% was achieved with the Densenet-121 model. The main difficulty in this work is the lack of a large database of lupus images.

Researchers Laura K Ferris, Jean A Harkes, Benjamin Gilbert, Daniel G Winger, Ksenia Golubets, Oleg Akilov, Mahadev Satyanarayanan used the DT classifier in their article "Computer-aided classification of melanocytic lesions using dermoscopic images" in order to assess the severity of skin lesions using dermoscopic images and evaluated the performance of the classifier [18]. The researchers calculated severity scores for 173 dermoscopic images of skin lesions with known histological diagnosis. A cutoff score was used to measure the sensitivity and specificity of the classifier. The study found that the classifier had a sensitivity of 97.4% for melanoma. The limitations of this study are that the image dataset was small and that it was retrospective, using available images selected by a dermatologist for biopsy.

The literature review revealed the following significant limitations and research gaps in the studies. In particular, the limited datasets for ML and DL-based skin disease classification and the lack of a complete system for preprocessing methods for medical images. For the effective performance of ML and DL models, image normalization, preprocessing, data augmentation, and their balance are important processes. Also, many studies have relied solely on the accuracy index to evaluate the performance of the model. Although accuracy is a crucial indicator, additional criteria including sensitivity, specificity, precision, and F1 score can provide a more comprehensive assessment of the model's performance. In addition, in some studies, the proposed models only achieved good results on a specific database. The fact that the accuracy of the model is not general in the detection of skin diseases limits the scope of the study.

III. Methodology. According to the results of the researches and the literature review, researchers mainly used the following five main steps in computer-aided diagnosis of skin diseases: image acquisition, pre-processing, segmentation, feature extraction, and classification. The most important steps in computer-aided diagnosis of skin diseases are segmentation and classification. The process flow architecture and common methodology for detecting and classifying skin diseases using image datasets using ML and DL techniques are illustrated in the following figure (Figure 2).

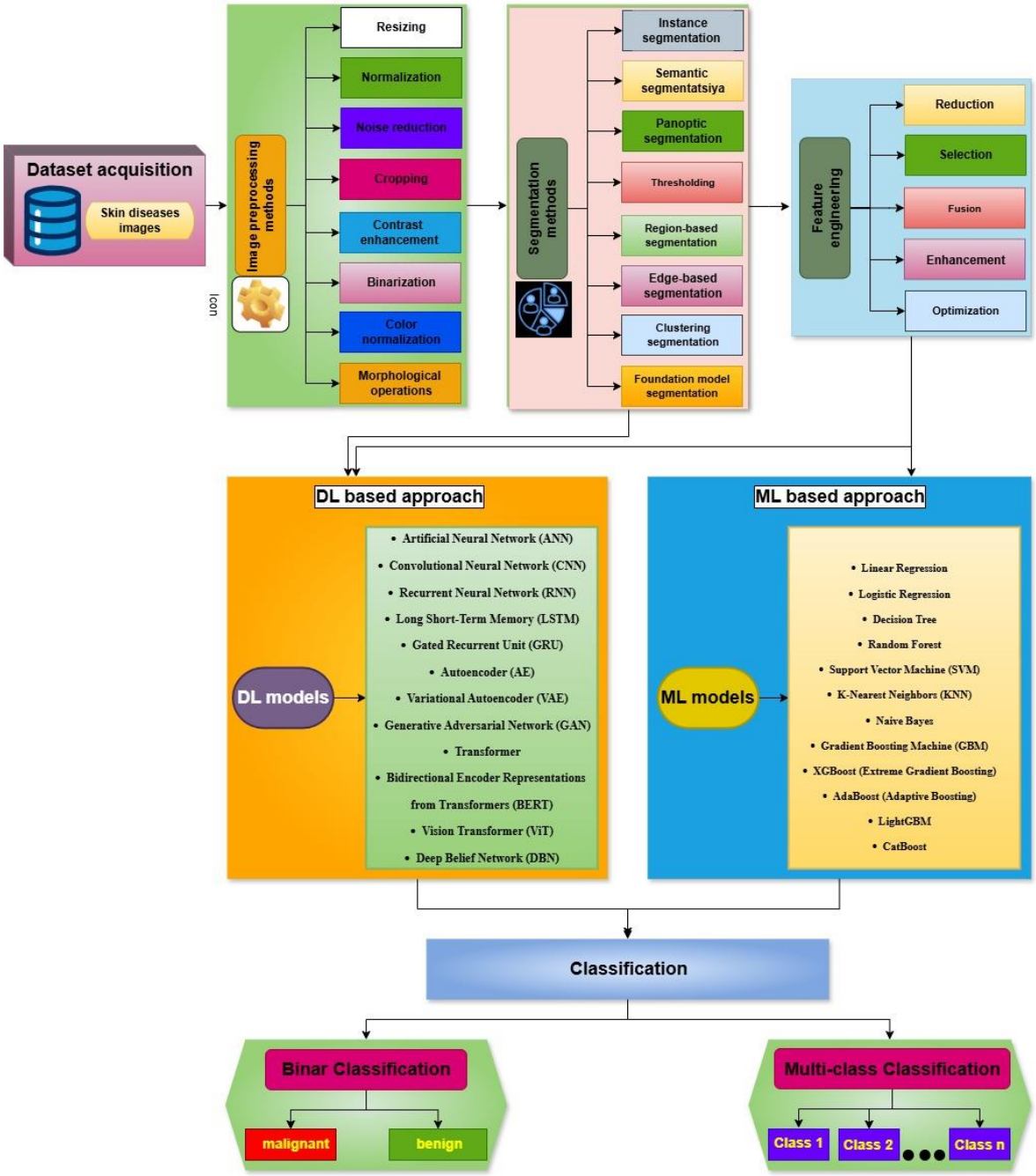


Figure 2. Process step flow architecture for skin disease classification

3.1. Image pre-processing. Medical image processing technologies play an important role in medicine for dermatological diagnostics and research. The process of processing medical images includes many methods to improve their quality and facilitate analysis. Pre-processing of medical images obtained from the skin surface is an important step to remove noise from the image and improve image quality. The main goal of this step is to improve the quality of skin disease images by removing unnecessary and irrelevant parts of the image. A good choice of processing technique can significantly improve the accuracy. The following is an analysis of pre-processing methods for acquired medical images.

Image Resizing. Image resizing refers to the process of changing the dimensions (width and height) of a captured digital image. The main goal of image resizing is to reduce or increase the size while preserving as much image detail and clarity as possible. There are several methods for resizing images, each with different approaches to preserving quality, sharpness, and image detail (Table 2).

Table 2. Image Resizing Methods.

	Methods	Formulas	Definitions
1.	Nearest Neighbor	$I'(x', y') = I(round(x'), round(y'))$	$I(x, y)$ be the intensity of the pixel at coordinates (x, y) in the original image. $I'(x', y')$be the intensity of the pixel at the new coordinates (x', y') in the resized image. $round(x')$ and $round(y')$ are the nearest integer coordinates in the original image.
2.	Bilinear Interpolation	$P(x,y) = (1-a)(1-b)P_{11} + a(1-b)P_{21} + (1-a)bP_{12} + abP_{22}$	P_{11}, P_{12}, P_{21}, P_{22}: The values of the four nearest pixels around (x, y). $a = x - x_1$: The fractional distance of x from the left pixel x_1. $b = y - y_1$: The fractional distance of y from the top pixel y_1.
3.	Bicubic Interpolation	$I(x,y) = \sum_{i=0}^{3}\sum_{j=0}^{3} w(i,x) * w(j,y) * I(x_i\| \ \|, y_j)$	$I(x_i, y_j)$: The intensity value of the surrounding pixels. $w(i,x) \wedge w(j,y)$: Cubic interpolation weights calculated for x and y, respectively. The summation iterates over the 4×4 grid of pixels.
4.	Lanczos Resampling	$I(x,y) = \sum_{i=-a}^{a}\sum_{j=-a}^{a} h(x-x_i) * h(y-y_i) * I(x_i\| \ \|, y_j)$	$I(x_i, y_j)$: Intensity value of the neighboring pixel at (x_i, y_j). a: The **Lanczos window size**. This determines the kernel size $(2a+1) * (2a+1)$. $h(d)$: The **Lanczos kernel**, which is defined as: $h(d) = \begin{cases} sinc(d) * sin\frac{d}{a}, \|d\| < a \\ 0, \wedge \|d\| \geq a \end{cases}$ $sinc(d) = \frac{sin(\pi d)}{\pi d}$, with $sinc(0) = 1$ by definition.

Normalization. Image normalization is an important process in machine learning and is the process of adapting images to certain standards in order to reduce errors in model performance. In this case, before entering images into the model, their pixel values are brought to a certain range. This range is usually from 0 to 255 for images with an 8-bit depth, where 0 represents black and 255 represents white. Normalization is performed to improve the contrast of the image or to standardize pixel values for further processing. As a result, the model is able to read the received data more stably and faster. At the same time, errors that occur during calculation are prevented. The following methods of image normalization are widely used in practice.

1. Min-Max normalization. In this method, the largest and smallest pixel values of the image are found and adjusted to a certain range. The general formula for normalizing images in the range [0; 1] is as follows:

$$Normalized_{value} = \frac{Pixel_{value} - Min_{value}}{Max_{value} - Min_{value}} \quad (1)$$

To normalize images in the range [-1; 1], the above formula is modified as follows:

$$Normalized_{value} = \frac{2 * Pixel_{value} - Min_{value}}{Max_{value} - Min_{value}} - 1 \quad (2)$$

Here,

- $Pixel_{value}$— the original pixel value in the image.
- Min_{value} — the minimum pixel value (or normalized range) in the image.
- Max_{value}— the maximum pixel value (or normalized range) in the image.

2. Z-score normalization. This normalization method assumes a Gaussian distribution of the data and transforms the features to a mean (μ) of 0 and a standard deviation (σ) of 1. The formula for Z-score normalization is:

$$Normalized_{value} = \frac{Pixel_{value} - \mu}{\sigma} \quad (3)$$

Here,

- $Pixel_{value}$ — the original pixel value in the image.
- μ — the mean value in the image.
- σ — standard deviation in the image.

This method is particularly useful when working with algorithms that assume normally distributed data, such as many linear models. Unlike the min-max scaling technique, this standardization technique is not limited to a specific range. This normalization technique mainly represents features in terms of the number of standard deviations away from the mean [19].

3. Mean normalization. In the mean normalization method, the pixel values of an image are adjusted to zero by adjusting them to the mean value of the data set. This ensures a balanced distribution of the image data.

$$Normalized_{value} = \frac{Pixel_{value} - \mu}{Max_{value} - Min_{value}} \quad (4)$$

Here,

- $Pixel_{value}$ — the original pixel value in the image.
- μ — the mean value in the image.
- Min_{value} — the minimum pixel value (or normalized range) in the image.
- Max_{value}— the maximum pixel value (or normalized range) in the image.

4. Decimal Scaling. Decimal scaling is a method of scaling image data by reducing a set of image data with a constant high intensity value to smaller manageable values. This method simplifies large pixel values by dividing them by powers of 10. This is an efficient way to scale data without complex calculations [20].

$$Normalized_{value} = \frac{Pixel_{value}}{10^j} \quad (5)$$

Here,

- $Pixel_{value}$ — the original pixel value in the image.
- *T*he scale factor *j* is the smallest integer, and it is defined as follows:: $10^j \geq |I_{max}|$

5. L2 Normalization. The L2 normalization method is also known as Euclidean normalization. The L2 norm (Euclidean norm) of pixel intensity is a method of scaling image data so that it is equal to 1. This method is commonly used in machine learning, deep learning, and image processing to normalize image features. The L2 normalization for pixel intensity is performed as follows:

$$Normalized_{value} = \frac{Pixel_{value}}{\|I\|_2} \quad (6)$$

Here,

- $Pixel_{value}$ — the original pixel value in the image.
- $\|I\|_2$ is the L2 norm of the pixel intensity and it is defined as: $\|I\|_2 = \sqrt{\sum_{i=1}^{N} I_i^2}$

Noise reduction. Noise in medical images can hinder the interpretation of medical scans and lead to misdiagnosis. Therefore, noise reduction in medical images is a very important task. The quality of medical images such as CT, MRI, X-ray, endoscopic images, and dermatological images is crucial for accurate diagnosis and treatment. Noise reduction methods should ensure the preservation of important details such as anatomical structures or pathological features, while eliminating distortions in the image that enter the model. The goal of image noise reduction is not only to remove noise, but also to preserve clinical details. The main requirements for image denoising [21, 22]:

- Smooth areas should remain smooth.
- Protect image boundaries (prevent blurring).
- Preserve texture information.
- Preserve overall contrast.
- Prevent new artifacts from appearing.

Edge detection. Edge detection is a basic image processing technique that is used to detect and locate the boundaries or contours of objects in an image. This technique is used to detect discontinuities

in brightness intensity in an image and extract the contours of objects in the image. The boundaries of any object in an image are usually defined as regions where the brightness intensity changes sharply. The main goal of edge detection is to distinguish these regions [23-25].

3.2. Segmentation. Image segmentation is a computer vision technique that aims to simplify and analyze digital images by dividing them into groups of pixels. Segmentation is the process of dividing or separating any digital image into multiple parts (segments). The goal of image segmentation is to present it in the simplest possible form and make it highly informative for analysis. There are several methods for image segmentation, with edge segmentation being one of the simplest and most effective. In this method, the pixels of the image are separated according to the contrast of the image, mainly based on intensity, and then a specific area of the image is divided into segments based on the application.

3.3. Feature extraction. After the segmentation step, feature extraction is the next major step, which is the input to neural classifiers. Data cannot be directly fed to a neural classifier for classification, only the extracted features are given as input. Feature extraction and feature selection are very laborious tasks that require a lot of time, effort, and human resources. Selecting the right features is very important because the performance of an ML classifier depends on the features. There are many feature extraction methods that can be used before feeding the dataset to an ML classifier for the classification task. These include stationary features, morphological features, wavelet-based features, color-based features, local and global features, and others. The most commonly used feature extraction methods for skin disease detection task are texture-based features, gray-level co-occurrence matrix (GLCM), asymmetry, boundary, color, and diameter (ABCD) rule-based features, principal component analysis (PCA) features, and geometric features. However, most researchers have used a combination of several features to achieve good classifier performance.

Feature extraction is the most important task in the classification task using ML classifier. However, this step is not important for DL-based classifier because DL classifiers extract features automatically. However, several researchers have used feature extraction techniques to further improve DL-based classifiers in the detection of various skin diseases. Some researchers have achieved good results in the classification of skin diseases using DL techniques without using any feature extraction methods.

3.4. Classification. ML-based classification has been proven to be one of the best methods for skin disease detection. Many researchers have identified skin disease types using ML-based classifiers, but various types of preprocessing, segmentation, and feature extraction methods are used in the pre-classification process. The research results show that many researchers have achieved even better accuracy using ML classifiers for skin disease classification than DL classifiers. The most effective and commonly used ML classifiers for skin disease detection are Support Vector Machine (SVM), Random Forest (RF), SVM with Radial basis kernel (SVM-RBF), Adaptive Artificial Neural Network (AANN), Radial Basis Function Neural Network (RBFNN), Ensemble Classifier (EC), Decision Tree (DT), K-Nearest Neighbor (KNN), etc.

DL is a highly trainable method that does not require any input features. Deep learning models are preferred for skin disease detection tasks, especially for detecting skin diseases from large datasets of images. The use of DL models has increased significantly in recent decades, especially for object detection and segmentation tasks. The most commonly used DL models for skin disease detection and classification tasks are Convolutional neural networks (CNN), Deep convolutional neural networks (Deep CNN), Long short term memory networks (LSTM), AlexNet, Residual Network (ResNet), UNet, VGG, Explainable Artificial Intelligence (EAI), EfcientNetB1, ShufeNet.

IV. Comparative analysis of results. The literature review and the studies conducted suggest that integrating ML and DL approaches for classifying skin diseases into dermatological practice will allow for early detection and treatment of diseases. Tables 3-4 below provide a comprehensive comparative analysis of the methods based on ML and DL algorithms proposed by researchers for classifying skin diseases. The tables analyze 20 studies with important parameters such as the type of disease, pre-processing methods for medical images, optimal classification methods, used database, number of data, percentage of highest scores (accuracy), and similar parameters.

Table 3. Classification of skin diseases using ML algorithms

n	Type of skin diseases	Preprocessing	Dataset	Data samples	Training data	Test data	Algorithm	Metrics	References	Year
1	BCC, SCC, melanoma	Automatic Grabcut Segmentation, digital hair removal (DHR), Gaussian filtering	ISIC 2019 challenge dataset	25331	80%	20%	SVM KNN DT	Accuracy = 95% 94% 93%	[26]	2022
2	Melanoma	Gaussian filter va median filter, k means clustering	ISIC 2019 challenge dataset	25000	70%	30%	Multi-class Support Vector Machine (MSVM)	Accuracy= 96.25%, precision= 96.32%	[27]	2020
3	Acne, cherry angioma, melanoma, psoriasis	Otsu's, for extracting features Gabor, Entropy, and Sobel	Private data	377	80%	20%	SVM KNN RF	Accuracy= 90.7% 84.2% 67.1%	[10]	2022
4	BCC, SCC, melanoma	Geodesic Active Contour (GAC)	International Skin Imaging Collaboration (ISIC)	1000	-	-	SVM KNN Naïve Bayes	Accuracy= 97.8%	[28]	2020
5	Melanoma	Dual-autoencoder	HAM10000	10015	80%	20%	Extreme Learning Machine (ELM)	Accuracy= 97.66%, precision= 97.68%	[29]	2024
6	BCC	Pre-trained CNN	ISBI 2016	1952	85%	15%	SVM	Accuracy= 88.02%	[30]	2023
7	Acne	-	Private data	3000	80%	20%	Logistic Regression	Accuracy= 67%	[31]	2019
8	Eczema, psoriasis,	Segmentation	DermIs DermQuest DermNZ	1800	-	-	SVM, Quadratic SVM	Accuracy= 94.74%	[32]	2019
9	Melanoma	ABCD rule	PH2	200	80%	20%	ANN SVM KNN DT	Accuracy= 92.50% 89.50% 82.00% 90.00%	[33]	2017
10	Lupus Erythematosus	LASSO dimensionality reduction	Private data	136	70%	30%	Xgboost	Accuracy= 82%	[34]	2023

All the studied literature on the detection of skin diseases was analyzed using the methods considered in the above tables. According to it, researchers M. Vidya, Maya V. Karki achieved high results in the diagnosis of skin cancer based on ML classifiers using 1000 image samples. The study used the Geodesic Active Contour (GAC) image preprocessing method. The evaluation indicators are high in all respects, and the accuracy of the SVM classifier is 97.8%.

In DL-based approaches, researchers Himanshu K. Gajera et al. developed the DenseNet-121 with multi-layer perceptron (MLP) model for melanoma classification and achieved the highest

accuracy acc 98%. The study used the PH2 dataset as a database. Preprocessing of medical images was performed using methods such as ABCD, Boundary Localization, Image Resize and Normalization.

Table 4. Classification of skin diseases using DL algorithms

Sn	Type of ases	Preproce	Dataset	Data	Train	Test	Algorithm	Metrics	Ref	Year
1	Melanom	data tion s	HAM100	10000	85%	15%	MobileNet he LSTM	Accuracy 84.12%	[35]	2021
2	BCC	data tion s	HAM100	10000	85%	15%	MobileNet he LSTM	Accuracy 96.63%	[35]	2021
3	Psoriasis	Resizing, tion	Private	813	80%	20%	ResNet50V esNet101V2, 2V2	Accuracy 91.41% 89.63% 90.24%	[36]	2024
4	Psoriasis	Resizing, tion	Private	813	80%	20%	CNN Model	Accuracy 93.29%	[36]	2024
5	Lupus	-	The Centre for ology	330	70%	30%	attention- NN, Stacked	Accuracy 95% 92%	[37]	2024
6	Eczema, a,	Resizing	Xiangya-	150223	-	-	Convolutio al Network	Accuracy	[38]	2023
7	Melanom	ABCD, on, Image and ation	PH2	200	70%	30%	DenseNet- multi-layer n (MLP)	Accuracy	[39]	2023
8	SCC,	-	ISIC	57536	80%	20%	Inception- 2 CNN	Accuracy 89.3%	[40]	2022
9	BCC,	Segmentat	HAM100	10000	80%	20%	S^2C-	Accuracy 97.41%	[41]	2022
10	Eczema,	Resizing, blur	DermNet [10000	27153	80%	20%	CNN	Accurasy 96.20%	[42]	2023

V. Conclusion. This research paper analyzes approaches based on ML and DL technologies for early detection and classification of skin diseases based on medical images. The study focuses on common and dangerous types of skin diseases. Different ML and DL architectures used for classification of skin diseases are discussed, and the processes leading up to the classification stage, that is, pre-processing methods for medical images, are studied. As a conclusion of the study, it is possible to create complex models that can analyze dermatological images with a high level of accuracy using ML and DL algorithms based on image analysis. These models are expected to support dermatologists with their ability to classify various changes in the skin with high accuracy and identify dangerous skin diseases. The use of computer-aided diagnostic systems can help dermatologists detect complex skin lesions at

early stages and make decisions. Future research should focus on classifying skin diseases based on AI approaches and improving the accuracy and robustness of models, and integrating these technologies into the current healthcare infrastructure.

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