АҚПАРАТТЫҚ-КОММУНИКАЦИЯЛЫҚ ТЕХНОЛОГИЯЛАР
ИНФОРМАЦИОННО-КОММУНИКАЦИОННЫЕ ТЕХНОЛОГИИ
INFORMATION AND COMMUNICATION TECHNOLOGIES

ҮЛГІНІ ТАНУ. КЕСКІНДІ ӨҢДЕУ
РАСПОЗНАВАНИЕ ОБРАЗОВ. ОБРАБОТКА ИЗОБРАЖЕНИЙ
PATTERN RECOGNITION. IMAGE PROCESSING

DOI 10.51885/1561-4212_2024_3_107
IRSTI 28.23.15

M.Zh. Ashimgaliyev[1], A.K. Zhumadillayeva[1], Ng. Yin Kwee[2], L.R. Suleimenova[3]
[1]L.N. Gumilyov Eurasian national university, Astana, Kazakhstan
E-mail: ashimgaliyev.medet@gmail.com
*E-mail: ay8222@mail.ru**
[2]Nanyang Technological University, Singapore
E-mail: mykng@ntu.edu.sg
[3]D. Serikbayev East Kazakhstan technical university, Ust-Kamenogorsk, Kazakhstan
E-mail: Lsuleimenova@edu.ektu.kz

LEVERAGING COMPUTER VISION IN THE MICROSCOPIC DIAGNOSIS OF SKIN CANCER THROUGH THE UTILIZATION OF BOTH MANUAL AND AUTOMATED FEATURES

ҚОЛМЕН ЖӘНЕ АВТОМАТТАНДЫРЫЛҒАН ФУНКЦИЯЛАРДЫ ПАЙДАЛАНУ АРҚЫЛЫ ТЕРІ ҚАТЕРЛІ ІСІГІНІҢ МИКРОСКОПИЯЛЫҚ ДИАГНОЗЫНДА КОМПЬЮТЕРЛІК КӨРУДІ ҚОЛДАНУ

ИСПОЛЬЗОВАНИЕ КОМПЬЮТЕРНОГО ЗРЕНИЯ В МИКРОСКОПИЧЕСКОЙ ДИАГНОСТИКЕ РАКА КОЖИ ПОСРЕДСТВОМ ИСПОЛЬЗОВАНИЯ РУЧНЫХ И АВТОМАТИЗИРОВАННЫХ ФУНКЦИЙ

Abstract. *The skin, our body's largest organ, shields us entirely. Among cancers, skin cancer, mainly prompted by sensitivity to sunlight's ultraviolet rays, is particularly fearsome. Melanoma stands out as the most perilous, originating in diverse ways. Detecting skin cancer early proves challenging for patients. Literature suggests the utilization of both manual and automated deep learning features in diagnosing skin cancer through traditional and deep learning methods. This study compares skin cancer diagnosis techniques, focusing on handcrafted and non-handcrafted features. Clinical features like the Menzies method, seven-point detection, asymmetry, border color and diameter, visual textures (GRC), local binary patterns, Gabor filters, random fields of Markov, fractal dimension, and oriental histography are investigated in the detection process. Parameters like the Jacquard index, accuracy, dice efficiency, preciseness, sensitivity, and specificity are assessed on benchmark datasets to compare techniques. The paper concludes by describing publicly available skin cancer datasets and highlighting remaining issues.*

Keywords: *Cancer, conventional versus deep learning, handcrafted versus non-handcrafted features, health systems, healthcare, skin melanoma.*

Аңдатпа*. Тері, біздің денеміздің ең үлкен мүшесі, бізді толығымен қорғайды. Қатерлі ісіктердің ішінде тері ісігі әсіресе күн сәулесінің ультракүлгін сәулелеріне сезімталдықпен туындаған қауіпті. Меланома әртүрлі жолдармен пайда болатын аурудың ең қауіпті түрі ретінде ерекшеленеді. Тері ісігін ерте анықтау пациенттер үшін қиынға соғады. Әдебиеттерде тері ісігін диагностикалауда дәстүрлі және терең оқыту әдістерін қолдана отырып, қолмен және автоматтандырылған терең оқыту мүмкіндіктерін пайдалануды ұсынады. Бұл зерттеуде қолмен және автоматтандырылған емдеу әдістеріне назар аудара отырып, тері ісігін диагностикалау әдістерін салыстырады. Анықтау процесі Мензис әдісі, жеті нүктелі анықтау, асимметрия, жиектің түсі мен диаметрі, визуалды текстуралар (GRC), жергілікті екілік үлгілер,*

Габор сүзгілері, Марковтың кездейсоқ өрістері, фракталдық өлшем және шығыс гистографиясы сияқты клиникалық белгілерді зерттейді. Джаккар индексі, дәлдік, текше тиімділігі, дәлдік, сезімталдық және ерекшелік сияқты параметрлер әдістерді салыстыру үшін эталондық деректер жиындарында бағаланады. Қағаз тері қатерлі ісігі туралы жалпыға қолжетімді деректер жиынтығын сипаттау және қалған қиындықтарды көрсету арқылы аяқталады.

***Түйін сөздер**: қатерлі ісік, дәстүрлі және терең оқыту, қолмен және автоматтандырылған функциялар, денсаулық сақтау жүйесі, денсаулық сақтау, тері меланомасы.*

***Аннотация**. Кожа, самый большой орган нашего тела, полностью нас защищает. Среди раковых заболеваний особенно опасен рак кожи, вызываемый главным образом чувствительностью к ультрафиолетовым лучам солнечного света. Меланома выделяется как наиболее опасная форма заболевания, возникающая по-разному. Раннее обнаружение рака кожи оказывается сложной задачей для пациентов. В литературе предлагается использовать как ручные, так и автоматизированные функции глубокого обучения при диагностике рака кожи с помощью традиционных методов и методов глубокого обучения. В этом исследовании сравниваются методы диагностики рака кожи, уделяя особое внимание ручным и неручным методам лечения. В процессе обнаружения исследуются такие клинические особенности, как метод Мензиса, семиточечное обнаружение, асимметрия, цвет и диаметр границы, визуальные текстуры (GRC), локальные бинарные паттерны, фильтры Габора, случайные поля Маркова, фрактальная размерность и восточная гистография. Такие параметры, как индекс Жаккарда, точность, эффективность кубиков, прецизионность, чувствительность и специфичность, оцениваются на эталонных наборах данных для сравнения методов. В заключение в документе описываются общедоступные наборы данных о раке кожи и освещаются оставшиеся проблемы.*

***Ключевые слова**: рак, традиционное и глубокое обучение, ручные и неручные функции, системы здравоохранения, здравоохранение, меланома кожи.*

Introduction. The prevalent form of cancer in humans is skin cancer, exhibiting a significant global rise. It can manifest anywhere on the skin and, if not treated promptly, often results in fatality. In 2012, global statistics reported 55,000 deaths among 232,000 individuals. The American Cancer Society disclosed that in 2015, 73,870 people were diagnosed with new melanomas, with 9,940 succumbing to melanoma skin cancer (Afza et al., 2019), (Al-Ameen et al., 2015). Common skin afflictions encompass acne, wrinkles, psoriasis, melanoma, and alopecia, with incurable melanoma being the most perilous, often culminating in death. The evolution of melanoma sometimes initiates from changes in size, itchiness, and color of a lesion. Early detection can elevate the survival rate to 100%, contrasting with a 59% survival rate for late detection, where deep melanoma exceeds three millimeters. Though non-melanomas are more prevalent, melanoma accounts for the majority of skin cancer deaths. Timely detection of malignant melanoma in its early stages significantly reduces mortality and morbidity (Khan, Javed, et al., 2019). Detecting malignant melanoma early could also lead to substantial cost savings compared to treating the disease at advanced stages. Melanoma's global incidence is rapidly increasing by 6% annually, currently standing at 15 per 0.1 million, and this trend persists (Javed, 2019). Skin cancer ABCD's (asymmetry, border, color, and diameter) are clinical features for pigmented lesions, and various image analysis methods have been devised to measure these features. Chemiluminescence-microscopy (ELM) has notably advanced early melanoma detection, with dermatologists utilizing ELM criteria to categorize pigmented skin lesions (Khan, Lali, et al., 2019), (Saba, Khan, et al., 2019).

Numerous research studies have demonstrated that employing accurate melanoma detection procedures can significantly improve the diagnosis ratio, showing an increase from 5% to 30% compared to naked-eye examinations (Premaladha & Ravichandran, 2016a).

Melanoma treatment typically involves radiotherapy and chemotherapy, similar to the approaches employed for critical conditions in breast, brain, lung, blood, and other types of cancers (Amin, Sharif, Raza, et al., 2020). Both radiotherapy and chemotherapy are strenuous processes. Detecting melanoma at an early stage becomes crucial to mitigate the need for these

arduous treatments and achieve successful therapeutic outcomes.

Ongoing biomedical imaging research is characterized by the introduction of innovative algorithms, and their outcomes are systematically compared using established benchmark datasets in the literature. The recently developed computer-aided diagnosis systems demonstrate increased intelligence, successfully tackling various challenges, including precise cancer segmentation and treatment. Consequently, evaluating the performance of these systems poses a challenge, making it challenging to draw definitive conclusions (Saba, Sameh, et al., 2019).

Materials and methods of research. In many computer-aided diagnosis systems, effectively detecting or distinguishing lesions from normal skin remains a challenge. Dermoscopy, a procedure involving digital image acquisition for high-quality data, is commonly used. However, various undesired details or artifacts may be present, including interlaced-video field misalignment, poor contrast, specular reflections, ruler markings, air bubbles, and hair. These unwanted elements diminish image quality and pose a hindrance to accurate skin lesion detection, particularly when the lesion closely resembles the surrounding skin.

Hence, a preprocessing step is introduced to enhance image quality by eliminating unwanted details like noise, including bubbles and hairs. If the preprocessing steps are not executed appropriately, there is a substantial risk of inaccurate segmentation and cancer recognition (Ejaz et al., 2018a).

Typically, dermoscopy images exhibit two distinct types of artifacts—firstly, acquisition artifacts like black frames, ink markings, rulers, reflections, and air bubbles. Secondly, cutaneous artifacts include elements such as hairs, vessels, blood, brain, and skin lines(Abbas et al., 2018). These unwanted details or artifacts disrupt the accurate skin lesion segmentation process, introducing inappropriate asymmetry, shape, color, and texture features that may lead to misinterpretation of the lesion features (Adeel et al., 2020), (Al-Badri et al., 2016a).

Various techniques are employed for image enhancement to eliminate artifacts or unwanted details in dermoscopy images. Methods like the dull Razor are applied to remove hairs from dermoscopy images. Additionally, various filters, including the adaptive Wiener filter, mean filter, Gaussian filter, median filter, and adaptive median filter, are utilized to eliminate different types of noise such as speckle noise, Poisson noise, salt-and-pepper noise, and Gaussian noise (Hussain et al., 2024).

Alternative techniques include edge enhancement, contrast enhancement, and illumination correction. To enhance contrast, various methods such as homomorphic filtering, FFT, histogram equalization, and histogram stretching can be applied(Iftikhar et al., 2017a).

Handcrafted features for traditional machine learning-based classification:

Classification is the procedure of determining the presence of a disease and identifying its type, where features play a pivotal role. An excess of features can bewilder classifiers, while too few features may result in misclassification. Occasionally, two or three discriminative features take precedence in the entire process (Khan, Lali, et al., 2019b). Feature extraction involves converting an image into a set of features, broadly categorized as handcrafted and non-handcrafted features. The former is utilized in conjunction with traditional machine learning techniques, while the latter is employed in deep learning applications (Javed, Saba, et al., 2019) .

The term "handcrafted" refers to manually devised and extracted features utilized in the training and testing of traditional machine learning techniques. Examples include shape-based features, histogram orientation gradient (Javed, Rahim, et al., 2019), texture-based Gabor wavelet transformation, local binary patterns, and statistical and geometrical features. Subsequently, optimal features are chosen through methods such as principal component analysis, genetic algorithms, and entropy-based techniques. Moreover, function fusion

procedures are employed to enhance classification accuracy (Al-Badri et al., 2016).

Color features. Termed chromatic features, these attributes find extensive use in biomedical image analysis, particularly in distinguishing healthy skin color from cancerous skin. Iftikhar et al. (2017b) underscored the significance of color in skin lesion identification. The Harris technique is employed, incorporating color and gray sampling in their methodology. A comparison between color-SIFT and SIFT features revealed that color-SIFT features exhibit superior performance in comparison to SIFT.

Clinical features. Various clinical features are derived from dermoscopic images for melanoma detection, including:

a. *Seven-point checklist.* In skin cancer classification, major and minor criteria play distinct roles. There are three major criteria, each assigned a score value of 2, while four points are allocated for the minor criteria, each with a score value of 1. If the total score reaches at least 3, the classification outcome is deemed malignant melanoma (Abbas et al., 2019). Table 1 illustrates that the presence of a blue-white veil, a standard pigmented network, atypical vascular patterns, and specific minor criteria such as abnormal streaks, abnormal pigmentation, irregular dots/globules, and regression structures are pivotal in diagnosing skin cancer.

b. *ABCD rule.* The ABCD rule in dermoscopy was the second algorithm introduced after pattern analysis (Ejaz et al., 2018). A multivariate study of 31 dermoscopic parameters led to the identification of four criteria as significant factors for diagnosing melanoma.

Table 1. Seven-point checklist method

S.no	Major criteria	Score	S.no	Minor criteria	Score
1	Atypical pigmentation network	2	4	Irregular streaks	1
2	Blue-white veil	2	5	Irregular pigmentation	1
3	Atypical vascular pattern	2	6	Irregular dots/globules	1
Note – compiled by the author based on (Saba, 2021)					

The ABCD rule for feature extraction is computationally less expensive compared to other scoring schemes like Menzies and the 7-point checklist. Additionally, it exhibits the highest consistency for clinical diagnosis. Table 2 details the ABCD rules and their corresponding results.

Table 2. Asymmetry, border color and diameter (ABCD) rules and result

Property	Description	Factor	Scoring
Asymmetry	Structure, colors and contour	1.3	0-2
Border	Eight segments	0.1	0-8
Color	Light-brown/tan, blue-gray, black-red, white and dark-brown	0.5	1-6
Diameter	Larger that 6mm	0.5	1-5
Categories	Total dermoscopy score		
Benign	Below from 4.76		
Suspicious	Between 4.76 and 5.45		
Malignant	Larger than 5		
Note – compiled by the author based on (Johr, 2002)			

a. Menzies scoring features. Introduced in 1996 and further developed in 2002, the Menzies scoring system was initially launched (Ejaz ch et al., 2019). This system relies on both negative features (symmetrical design, single color) and positive features (white-blue

mask, several brown dots, pseudopod, radial broadcasting, scar-like depigmentation, several colors (5-6), many blue/grey dots, spent network). For a melanoma diagnosis, the presence of one or more positive characteristics in the image is required, while for non-melanoma, the absence of harmful characteristics is necessary, as illustrated in Table 3. Both melanoma and non-melanoma have a limit to the existence of one or more beneficial features. Negative features should be absent, as indicated in Table 3.

Table 3. Menzies scoring features list

Negative features for non-melanoma	Positive features for melanoma
Symmetrical pattern	Multiple (5-6) colors
Signal color	Blue-white veil Radial streaming Multiple blue/grey dots Multiple brown dots Broadened network Pseudopods Scar-like depigmentation
Note – compiled by the author based on (Saba, 2021)	

Traditional machine learning. The inception of computer-aided cancer diagnosis through bioimage analysis began a few decades ago, aiming to assist healthcare practitioners and paramedical staff in the clinical decision-making process (Saba et al., 2018).

Ramya et al. (2015) employed an adaptive histogram equalization technique and a Wiener filter for preprocessing, coupled with an active contour segmentation mechanism. GLCM-based features were extracted, and an SVM binary classifier was utilized to classify skin cancer as malignant or benign. The experimental setup involved extracting images using a digital camera.

In another approach, Leguizamon Correa et al. (2015) developed a technique to differentiate skin lesions as malignant or benign using dermoscopic images. Their method encompassed specific modules: preprocessing, lesion segmentation, lesion feature extraction, and classification. In the preprocessing step, unwanted details such as hairs were removed, and segmentation aimed to identify the region of interest (ROI) for further processing. For feature extraction, the ABCD rule and an SVM classifier were employed for classification purposes. Experimental results, based on a dataset of 104 dermoscopy images, revealed a precision of 83.33%, 95% sensitivity, and an accuracy of 90.63%. However, it's noted that the presented system did not achieve promising results. Various feature extraction and classification methods are illustrated in Figure 1.

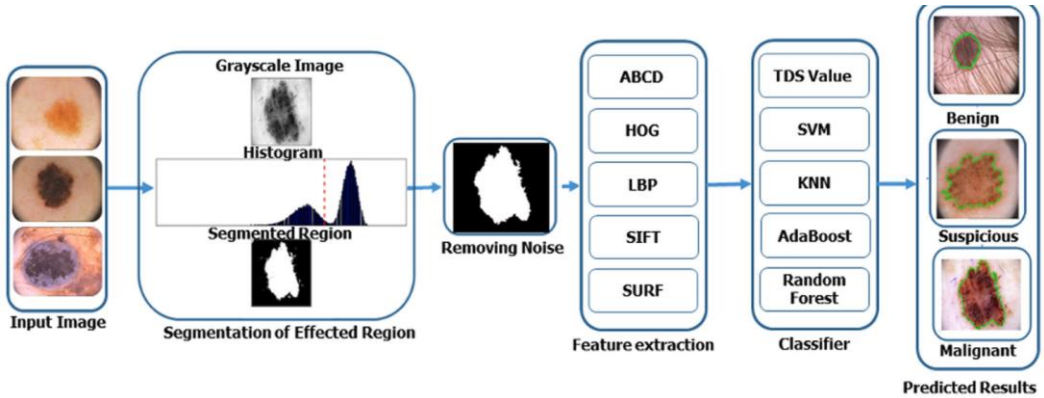

Figure1. Conventional ML framework for skin cancer classification

Note – compiled by the author based on (Saba, 2021)

Premaladha & Ravichandran (2016) proposed an effective method for melanoma classification and prediction within a Computer-Aided Diagnosis (CAD) framework. They utilized a Median filter and Contrast Limited Adaptive Histogram Equalization approaches to enhance image consistency. Normalized-Otsu was employed to mitigate variable illumination and facilitate skin lesion segmentation. Fifteen features were extracted from the segmented images and fed into the hybrid classifier, which integrates neural networks centered on a hybrid AdaBoost-SVM and deep learning. The validation and testing of approximately 992 images belonging to benign and malignant lesions achieved a classification precision of 93%. However, it's noted that their hybrid strategy entails a longer time consumption during the training and testing stages.

Taufiq et al. (2017) introduced a mobile-based healthcare system for real-time skin cancer detection. Image processing and computer vision methods were utilized, incorporating a Gaussian filter for noise removal and the Grab Cut method for image segmentation. Various features, including eccentricity, perimeter, and area, were extracted from the segmented image and fed into an SVM classifier for classification. The system achieved specificity and sensitivity rates of 75% and 80%, respectively, but further improvement is deemed necessary.

Dalila et al. (2017) proposed an automatic approach considering three types of characteristics to describe malignant lesions, employing an Ant colony-based segmentation algorithm. The selected characteristics included geometric properties, texture, and relative colors, with K-nearest neighbor (KNN) and Artificial Neural Network (ANN) classifiers. Experiments on the ISIC skin cancer dataset resulted in an accuracy of 85.22% with KNN and 93.60% with ANN.

Hamzah et al. (2018) detected melanoma-type skin cancer using a combination of Canny edge detection and watershed marker control techniques on digital images. The ABCD method was utilized to extract features from the digital images acquired by a digital camera. Experiments conducted on the PH2 dataset reported an accuracy of 9/10 for melanoma and 8/10 for non-melanoma.

Akram et al. (2018) presented their contribution in three stages. In the first stage, they utilized multilevel contrast stretching algorithms for foreground separation from the background. The second stage involved the use of a threshold-based method for selecting texture-feature analysis, central-distance, boundary-connections, and related labels. In the third stage, they introduced enhanced dimensionality reduction and feature extraction criteria that fused conventional and recent feature extraction methods. Experiments on the ISBI dataset yielded results with 99.2% accuracy, 99.2% sensitivity, 99.4% specificity, 99.4% precision, 0.6 NPV, 0.8 FNR, and 0.005 FPR achieved on M-SVM.

Murugan et al. (2019) implemented a watershed segmentation technique to segment interesting areas from the image. Subsequently, various features such as GLCM, ABCD rule, and shapes were extracted from the segmented image. These extracted features were then classified using SVM, KNN, and Random Forest classifiers. In the classification, the SVM classifier demonstrated the best result for skin cancer detection. Experiments on the ISIC dataset reported an accuracy of 89.43%, sensitivity of 91.15%, and specificity of 87.71%. However, predicting the result in a real-time scenario is considered challenging.

Recently, Balaji et al. (2020) introduced a dynamic graph cut algorithm and a Naive Bayes classifier for the segmentation and classification of skin diseases using the ISIC 2017 dataset. They examined three types of cancers: keratosis, melanoma, and benign, reporting classification accuracies of 92.9%, 91.2%, and 94.3%, respectively.

Qin et al. (2020) employed a Generative Adversarial Network (GAN) for skin lesion classification. They enhanced the GAN using the data augmentation concept. Experimental results reported an average precision of 96.6%, specificity of 74.3%, sensitivity of 83.2%, and

an accuracy of 95.2%.

Upon reviewing the literature, it is evident that numerous approaches are being introduced for early-stage skin cancer diagnosis using traditional machine learning. However, traditional machine learning techniques face two main limitations. Firstly, they require manual feature extraction, and secondly, they may not yield fruitful results for large datasets (Noman et al., 2018). Table 4 provides comparisons of conventional machine learning techniques using handcrafted features for skin cancer diagnosis.

Table 4. Conventional machine learning techniques using handcrafted features for skin cancer diagnosis

Reference	Approach	Data sets	Results (%)
Murugan et al. (2019)	Features are extracted using shape, GLCM and ABCD rule. ISIC For classification KNN, random Forest and SVM classifiers are used.	ISIC	89.43 (accuracy) 91.15 (sensitivity) 87.71 (specificity)
Afifi et al. (2020)	FPGA platform, monolithic SVM HLS IP and dynamic cascade SVM	Clinical data set	97.9 (accuracy)
Hamzah et al. (2018)	Watershed marker control canny edge detection methods and the features are extracted using ABCD rules	PH2	With melanoma 9/10 accuracy And with non-melanoma 8/10 accuracy
Akram et al. (2018)	From a segmented image, different features are extracted that is, color, shape, and clinical. The extracted features are combined to employ serial methods and further reduce it by using NCA method. Finally, for classification M-SVM is used.	SBI 2016	99.2 (accuracy) 99.2 (sensitivity) 99.4 (specificity) 99.4 (precision) 0.6 (NPV) 0.8 (FNR) 0.005 (FPR) is achieved on M-SVM
Bakheet (2017)	Features are extracted by using HoG feature descriptor and SVM is used for classification	Atlas	97.32 (accuracy) 98.21 (sensitivity) 96.43 (specificity)
Wahba et al. (2017)	The fusion of gray-level-difference and bi-dimensional-empirical-mode-decomposition methods are used for features extraction and quadratic-SVM	ISIC	100 (accuracy) 100 (sensitivity) 100 (specificity) 1 (F-measure)
Taufiq et al. (2017)	Hair removing is performed by Gaussian filter, for region-of-interest grab cut segmentation method is used, features like eccentricity, area and perimeter are extracted and SVM is used for classification	ISIC	With melanoma 80 (accuracy) And with non-melanoma 75 (accuracy)
Dalila et al. (2017)	Relative colors, texture and geometrical features are extracted and used two classifiers KNN and ANN	ISIC	85.22 (accuracy) using KNN extracted And 93.60 (accuracy) using ANN

Non-handcrafted features for deep learning-based classification

Presently, researchers have explored the potential of Artificial Intelligence (AI) to improve or supplement existing screening methods. Convolutional Neural Networks (CNNs) are commonly utilized in biomedical image analysis and cancer detection. Furthermore, approaches based on Convolutional Neural Networks (CNNs) have demonstrated an effective skin cancer

detection process (Mittal et al., 2020), (Ramzan et al., 2020). The key advantage of CNN-based approaches lies in their automatic feature extraction and training capabilities with automatic feedback. Figure 2 provides a visual representation of the CNN deep learning model.

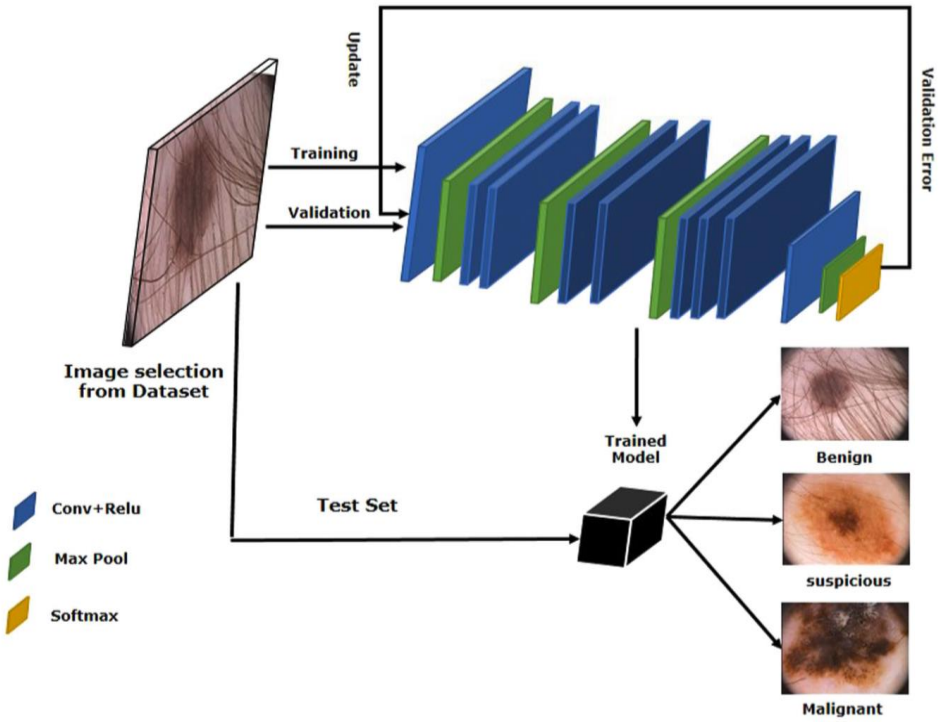

Figure 2. CNN architecture for skin cancer classification
Note – compiled by the author based on (Saba, 2021)

Majtner, Yildirim Yayilgan, et al. (2016) extracted Adhoc handcrafted features from images and integrated them with an in-depth learning method responsible for further learned functions. They subsequently classified the entire feature set into malignant or benign lesions using a deep learning strategy, reporting an accuracy of 82.6%, sensitivity of 53.3%, specificity of 89.8%, and an area under the curve of 78% on the ISIC dataset. However, the specificity and sensitivity rates seem relatively low.

Rodrigo-Nicolás et al. (2018) utilized 19,398 images to develop a Computer-Aided Diagnosis (CAD) system, achieving an average specificity and sensitivity of 81.3% and 85.1%, respectively. Various approaches have been proposed recently to compare the performance of the Convolutional Neural Network (CNN) classifier with dermatologist performance. Brinker et al. (2019) classified malignant skin cancer using CNN with 12,378 dermoscopic images on the publicly available ISIC dataset, achieving 92.8% sensitivity and 61.1% specificity. However, the model's training time and the requirement for a powerful GPU make the system less feasible.

Recently, Saba, Sameh, et al. (2019) introduced an automatic skin lesion diagnosis solution using a Deep Convolutional Neural Network (DCNN). Their approach involves three main steps: contrast enhancement, lesion boundary extraction with CNN, and features extraction with the Inception V3 model. Experiments on ISBI 2016, ISBI 2017, and PH2 datasets achieved accuracies of 95.1%, 94.8%, and 98.4%, respectively. Table 5 provides comparisons of deep

learning techniques using non-handcrafted features for skin cancer diagnosis.

Result and discussion. Benchmark datasets play a crucial role in conducting experiments and comparing results in the state-of-the-art. Therefore, this section introduces widely used standard datasets for skin cancer experiments and performance metrics to evaluate techniques reported in the current state of the art (Amin et al., 2019).

- ISIC Dataset: The ISIC dataset is a product of the ISIC Melanoma Project and is freely available online for research purposes. It comprises approximately 3,000 dermoscopic high-resolution images for training/testing, accompanied by human-validated metadata. However, the size of the images is not fixed, as different visual sensors were employed in the procurement process (Amin et al., 2018).
- Asan Dataset: The Asan dataset originates from the Dermatology Department at the Asan Medical Center. Spanning from 2000 through 2016, a total of 598,854 clinical photographs were captured. The Asan dataset comprises 12 forms of skin diseases specifically selected for its establishment.
- ISBI 2016 Dataset: The ISBI 2016 skin lesion dataset comprises 1,279 RGB images, with 273 classified as benign and 1,006 as melanomas. This challenge involves various tasks, including segmentation, identification of characteristics, and grouping lesions into the required categories. The dataset allocates 900 images for the training set and 379 images for the testing process (Amin et al., 2018).
- ISBI 2017 Dataset: The ISBI 2017 challenge incorporates 2,750 DY RGB images with a resolution ranging from 296 to 1,456. Among these, 2,233 images are classified as benign, while 517 images are categorized as melanomas. For the theoretical assessment, the preparation phase utilizes 2,000 images, with the remaining 750 images reserved for evaluating the proposed systems (Amin, Sharif, Yasmin, et al., 2020).
- UMCG Dataset: The UMCG dataset comprises 170 nondermoscopic images, including 70 melanoma and 100 benign images sourced from the University Medical Center Groningen (UMCG) Department of Dermatology's digital image collection (Nasr Esfahani et al., 2016a).

Table 5. Deep learning techniques using non-handcrafted features for skin cancer diagnosis

Reference	Methodology	Data set	Results (%)
Kadampur & Al Riyaee (2020)	Convolutional Neural Network (CNN)	HAM10000	99.77 (AUC)
Brinker et al. (2019)	Convolutional Neural Network (CNN)	ISIC	92.8 (sensitivity) 61.1 (specificity)
Saba, Sameh, et al. (2019)	HSV color transformation and FlLpF for image enhancement, the boundary is extracted using XOR and color CNN method, transfer learning using inception V3 and fusion using hamming distance (HD) approach	ISBI 2016 ISBI 2017 PH2	95.1 (accuracy) 94.8 (accuracy) 98.4 (accuracy)
Sahu et al. (2018)	Deep Convolution Neural Network (DCNN)	ISIC	82 (melanoma) 68 (basal cell carcinoma) 83 (intraepithelial carcinoma) 30 (squamous cell carcinoma) 65.7 (overall

			accuracy)

End of table 5

Han et al. (2018)	Finetuned ResNet-152 model	Asan data set, MED-NODE data set, and atlas site images	86.4 ± 3.5 (sensitivity) 85.5 ± 3.2 (specificity) 91 ± 0.01 (AUC)
Rundo et al. (2018)	SC-Cellular Neural Networks are used for segmentation, ABCDE features are extracted and Stacked Deep Autoencoder as classifiers	PH2	98 (sensibility) 98 (specificity)
Ünver & Ayan (2019)	Data augmentation and CNN model are used for feature extraction and classification	ISIC	81 (accuracy) 0.41 (loss)
	Convolution Neural Network (CNN)	Clinical images	72.1 (accuracy) 91 (AUROC)
Conoci et al. (2017)	SC-Cellular Neural Networks are used for segmentation and preprocessing, ABCDE features are extracted, and pre- trained Levenberg Marquardt Neural Network are used for decision	PH2	97 (sensibility) 95 (specificity)
Nasr Esfahani et al. (2016)	Pre-trained Convolutional neural network (CNN)	UMCG	81 (accuracy) 81 (sensitivity) 80 (specificity) 75 (PPV) 86 (NPV)
Xie et al. (2017)	A neural network ensemble model employed using lesion extraction, color, texture, border features	ISIC	94.17 (accuracy) 95.00 (sensitivity) 93.75(specificity)
Majtner, Lidayova, et al. (2016)	Deep learning method combined with handcrafted RSurf features and local binary patterns	ISIC	82.6 (accuracy) 53.3 (sensitivity) 89.8 (specificity) 78.0 (AUC)

Performance metrics. Comparing results in the state of the art is challenging due to variations in datasets, experimental setups, and methodologies employed by researchers (Afza et al., 2019). Nonetheless, researchers commonly utilize the following metrics to evaluate techniques for skin cancer diagnosis and to facilitate model comparisons:

$$Sensetivity\ SE = \frac{TP}{TP + FE}$$

$$Specitivity\ SP = \frac{TP}{TN + FP}$$

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

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

$$Positive\ Predictive\ Value\ (PPV) PPV = \frac{TP}{TP + FP}$$

$$Negative\ Predictive\ Value\ (NPV) NPV = \frac{TP}{TN + FN}$$

$$Dice\ coefficient = \frac{2.TP}{2.TP + FN + FP}$$

$$Jaccard\ index\ JA\ =\ \frac{TP}{TP+FN+FP}$$

Conclusion. The early detection of cancer growth is pivotal for effective classification and treatment, potentially saving lives. Trained computerized systems offer the capability to autonomously identify cancer from a vast array of medical images, eliminating the need for human intervention. This article provides a comprehensive comparison of the automated skin cancer diagnosis process, employing both handcrafted and non-handcrafted features with traditional machine learning and deep learning methods. Various imaging modalities reported in the literature are thoroughly analyzed and compared using benchmark datasets. However, challenges arise in the image acquisition process due to issues such as poor contrast, inconsistent lighting, and unavoidable noise. Moreover, the efficiency of reported techniques is compromised by variations in aspect, structure, volume, and location of the region of interest. This review encompasses a four-step approach for skin cancer detection, incorporating both conventional and deep learning models.

Another significant challenge lies in comparing skin lesion classification approaches, as individual works differ in the dataset utilized, the scale of training/test data, and infrastructure. To address this issue, the ISIC Melanoma Project has been instrumental since 2016, establishing a freely available dermatoscopic skin lesion image database to serve as a benchmark for education and research. The project also introduces an annual competition that focuses on solving a specifically identified issue. Engaging in further study that contrasts itself with this benchmark to achieve a higher rating of procedures in the state of the science would be beneficial.

A significant challenge in this research area is the establishment of extensive public image collections that accurately represent the entire global population. The predominant skin lesions in the ISIC dataset mainly come from light-skinned individuals, predominantly from Western populations. Simultaneously, for CNNs to adeptly generalize and provide accurate classification for dark-skinned individuals, they need exposure to a sufficient number of images from individuals of diverse skin tones, including those from the East. This crucial diversity in the training data is essential to enable the network to effectively learn and summarize features related to dark skin tones.

This research serves as a valuable resource for new researchers, aiding them in identifying existing gaps and limitations that require further improvement within this research area. Additionally, the study highlights specific gaps that warrant attention from future researchers. The brief discussion on various datasets, their public availability, and characteristics will assist new researchers in selecting the most suitable dataset for their experiments. Furthermore, the inclusion of clinical details such as age, gender, color, skin texture, and anatomical location as inputs for classifiers is recommended to enhance accuracy. This additional data proves advantageous for dermatologists in their decision-making processes, making it a crucial consideration for future work in this field.

Conflicts of Interest. The authors declare no conflict of interest.

Acknowledgements. The research data was sponsored by the Science Committee of the Minister of Science and Higher Education of the Republic of Kazakhstan (Grant No.of the research fund AP14869848 Software development and test suite preparation in Competitive Programming)

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Information about authors

Ashimgaliyev Medet Zhumabayevich – doctoral student, L.N.Gumilyov Eurasian national university, Astana, Kazakhstan, ashimgaliyev.medet@gmail.com

Zhumadillayeva Ainur Kanadilovna – Candidate of technical sciences, Associate professor, L.N.Gumilyov Eurasian national university, Astana, Kazakhstan, ay8222@mail.ru , +77025295999

Ng Yin Kwee – Ph.D, Nanyang Technological University, Singapore, myknq@ntu.edu.sg

Suleimenova Laura Rakhmetollanovna – PhD, deputy dean, D. Serikbayev East Kazakhstan technical university, Ust-Kamenogorsk, Kazakhstan, E-mail: lsuleimenova@edu.ektu.kz, ORCID: 0000-0003-0770-8549, +77772956203