Intelligent Medicine 3 (2023) 180–190

Contents lists available at ScienceDirect

Intelligent Medicine

journal homepage: www.elsevier.com/locate/imed

Review

State-of-the-art machine learning techniques for melanoma skin cancer detection and classification: a comprehensive review

Harsh Bhatt[1], Vrunda Shah[1], Krish Shah[2], Ruju Shah[1], Manan Shah[3,*]

[1] Department of Computer Science, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India
[2] Dhirubhai Ambani Institute of Information and Communication Technology, Gandhinagar, Gujarat, India
[3] Department of Chemical Engineering, School of Energy Technology, Pandit Deendayal Energy University, Gandhinagar, Gujarat, India

ARTICLE INFO

Keywords:
Machine learning
Skin cancer
Classification

ABSTRACT

Skin cancer is among the most common and lethal cancer types, with the number of cases increasing dramatically worldwide. If not diagnosed in the nascent stages, it can lead to metastases, resulting in high mortality rates. Skin cancer can be cured if detected early. Consequently, timely and accurate diagnosis of such cancers is currently a key research objective. Various machine learning technologies have been employed in computer-aided diagnosis of skin cancer detection and malignancy classification. Machine learning is a subfield of artificial intelligence (AI) involving models and algorithms which can learn from data and generate predictions on previously unseen data. The traditional biopsy method is applied to diagnose skin cancer, which is a tedious and expensive procedure. Alternatively, machine learning algorithms for cancer diagnosis can aid in its early detection, lowering the workload of specialists while simultaneously enhancing skin lesion diagnostics. This article presented a critical review of select state-of-the-art machine learning techniques used to detect skin cancer. Several studies had been collected, and an analysis of the performance of k-nearest neighbors, support vector machine, and convolutional neural networks algorithms on benchmark datasets was conducted. The shortcomings and disadvantages of each algorithm were briefly discussed. Challenges in detecting skin cancer were highlighted and the scope for future research was proposed.

1. Introduction

Skin cancers are caused by the formation of abnormal cells that, depending on their nature and intensity, may infiltrate or spread to different areas of the body. Since our skin is the most exposed organ to environmental toxins, it is the most vulnerable. As a result, skin cancer is the most common and common of all cancers. In the United Kingdom, approximately 46,000 new cases of skin cancer are reported each year.

Skin cancer can be divided into three types: basal cell skin cancer (BCC), squamous cell skin cancer (SCC), and melanoma. The first two types of skin cancer are classified as non-melanoma and rarely lead to death. The most lethal type of skin cancer is melanoma. UV radiation from the sun is the main cause of major skin cancers. Fair-skinned races have a higher risk of skin cancer than dark-skinned races, which could be due to the excellent protection provided by pigment in the layers that are directly exposed [1].

Melanoma is a tumor that originates in melanin-producing cells and is found primarily on the skin, eyes, nerve centers, and meninges. Melanoma is more likely to be cured if diagnosed early, despite the highest rate of increasing incidence among all types of skin cancer [2]. According to one study, the timely identification of early-stage skin cancer reduced the mortality rate by 90% [3]. Patients in stage I of the disease, for example, have a 10-year overall survival chance from 94% to 98%, while patients in stage IV have an estimated 10-year overall survival of just 10% to 15%. Melanoma is more common in some populations than in others. Recognizing these groups can help prevent these high-risk situations [4].

Typically, the biopsy procedure is used to identify skin cancer. This procedure requires extracting a sample of a putative skin lesion for medical tests to determine whether it is malignant. However, it is a rigorous, painful, and time-consuming process. Computer-based technology makes it possible to diagnose skin cancer symptoms using a rapid, more convenient, and affordable, approach [5]. The primary goal of such systems is to perform a preliminary assessment of suspicious skin lesions using high-quality histopathologically-confirmed clinical images and machine learning techniques. However, it cannot replace the crucial role of histopathology in tumor diagnosis, but the development of high-quality

* Corresponding author: Manan Shah, Department of Chemical Engineering, School of Technology, Pandit Deendayal Energy University, Gandhinagar, Gujarat, India (Email: manan.shah@spt.pdpu.ac.in).

https://doi.org/10.1016/j.imed.2022.08.004
Received 27 June 2022; Received in revised form 22 August 2022; Accepted 25 August 2022

diagnostic tools can significantly help screen for malignant neoplasms in their early stages in areas where medical resources and medical practitioners are lacking.

Several noninvasive alternatives have stimulated researchers to identify skin cancer symptoms and establish whether they are caused by melanoma. Because of its non-invasive nature, image processing has been widely proposed for the detection of melanoma skin cancer. It has developed into a useful diagnostic tool to accurate interpretation of medical images, allowing patients to receive prompt and successful treatment. Image processing provides experts with an instantaneous diagnostic tool, allowing them to track changes in the patient's condition over time, provide photos for training and presentation, and compare images quickly. It may also be cost-effective for hospitals [6].

Although dermoscopy can be used to inspect the hypodermis without surgery, excellent results require extensive dermatology training and experience. Unfortunately, this approach does not provide a definitive diagnosis of melanoma, especially in the early stages. As a result, an automatic diagnostic tool becomes an unavoidable requirement.

When classifying lesions, Baldrick et al. compared expert opinion with artificial neural networks. The computer program reported a sensitivity of 95% and a specificity of 88%, while dermatologists reported a similar sensitivity and specificity score of 95% and 90%, respectively [7]. Based on these results, automated systems can be potentially utilized in the areas of cancer detection.

Modern computer-based technologies have widely used machine learning. It is a wide and rapidly evolving branch of artificial intelligence that enables computers to learn and develop automatically without having to be explicitly programmed [8]. The technology stems from studying pattern recognition and computational learning theory and has found a place in an abundance of applications in recent decades.

In general, the learning methods used by machine learning can be classified into Supervised, Unsupervised, and Reinforcement learning. Supervised learning uses previously known input features and output datasets to learn and obtain a common relationship. In Unsupervised learning, the input dataset is provided, but the corresponding outputs are not provided. It is left to the machine to work on these data and form meaningful insights while in Reinforcement learning, artificial intelligence encounters a game-like scenario. To obtain the solution to the game, the computer uses trial and error. Artificial intelligence is given either rewards or penalties for the choices it makes to accomplish what the programmer desires. Its purpose is to increase the overall rewards as much as possible.

For cancer prediction, a mostly supervised learning approach is employed that makes use of algorithms for classification based on conditional decisions or probabilities. The most common algorithms or methodologies include decision trees [9], convolutional neural networks (CNN), support vector machine (SVM), and k-nearest neighbors (KNN). This article will review the application of these three algorithms in the detection of skin cancer.

CNN is a deep learning method that applies image processing techniques and inferences in contrast to classical machine learning methods [10]. CNN models generate high-precision output and are efficient in solving complex problems. They can be applied using different mathematical learning methods [11].

Support vector machines (SVMs) are used for classification and regression [12]. Decision planes that determine decision boundaries are used in this method [6]. It is a supervised learning algorithm, which means that it uses a labelled dataset for training purposes [13].

The k-nearest neighbor classifier is one of the simplest image classification methods. KNN is mostly used for pattern recognition. This method categorizes unidentified data points by identifying the most similar clusters among the k-closest samples.

To obtain the final model it is important to go through several phases, which includes preprocessing methods in which hair removal, shade removal, and glare removal are done. By minimizing these variables, we obtain a better idea of parameters such as the color, texture, and shape of the tumor. The next step is feature extraction and segmentation. The last and final step includes model making and training, in which various algorithms are applied to obtain an output [14].

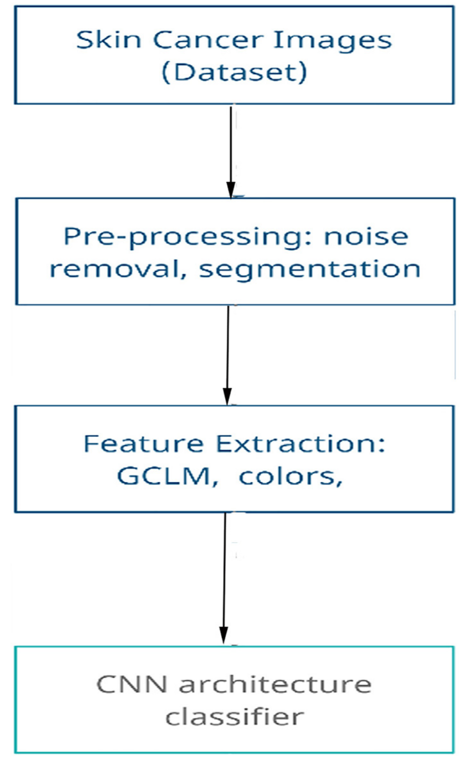

Figure 1. Block diagram showing skin cancer classification using CNN.

Artificial intelligence has shown promise in numerous experimental studies, especially in the diagnosis of skin cancer. Bringing these results to the clinic is the next logical step. AI-based systems, particularly deep learning-based, are rapidly entering the medical industry. Layered mathematical models are used to handle enormous datasets to accomplish a given task, such as automatic pattern recognition [15].

Deep neural networks (DNN), CNN, long- and short-term memory (LSTM), and recurrent neural networks (RNN) are the most widely used deep learning architectures applied to clinical medicine for the detection of cancer cells [16]. These models have also been used successfully in the classification of skin cancer [17] (Figure 1).

Based on the characteristics of the image, computer processing may be used to classify lesions. This process utilizes methods such as morphological transformations and filtering, among others, to evaluate the data available from various dermatoscopic images fed into the program. Deep learning is used to identify unidentified patterns in the training dataset [18].

From diagnosis to personalized therapy, machine learning offers a greater likelihood of improving dermatology practice. Recent developments in accessing large datasets (e.g., electronic medical records, image databases), faster computation, and less expensive data storage have fueled the use of sentient intelligence machine learning algorithms in dermatology [19].

An Internet of things (IoT)-based, virtualized remote skin monitoring system may undoubtedly help with autonomous, real-time diagnosis and skin disease prevention. IoT-based skincare services are projected to be cost-effective, improve quality of life and provide genuine monitoring. This effort will help create a perfect skin care platform, helping to identify and diagnose skin diseases early, treat skin problems, and improve quality of life [20].

2. Convolution neural network in skin cancer detection

A CNN is a deep learning technique and a class of artificial neural networks applied to analyze visual image-based data. Similar to artificial neural networks, CNNs learn the features of the training set to differentiate the classes of the test set using feedforward and backpropagation [21]. CNNs provide superior performance compared to basic machine learning techniques but are also more computationally demanding. CNNs commonly consist of three types of layers, namely, a convolutional layer, a pooling layer, and a fully connected layer, generally appearing in that order. The higher the number of layers, the greater the complexity of the network and the greater the pattern identification.

The primary usage of CNNs is seen in vision-based applications. Fields of study that require processing to be performed on images such as fingerprints, tumor cells, flower species, duplicate product detection, and face recognition incorporate the usage of CNN to work on still images. CNNs are also used in video processing, in which the video is broken down into frames to produce individual images. This usage can be seen primarily in real-time applications, such as autonomous vehicles. CNNs also contribute to historical fields. Provided sufficient data are available, CNNs can be used to classify historic texts, artefacts, and collections. CNNs are also used to understand the climate and how its drastic changes can be reduced. CNNs are also used in speech processing applications.

Majtner et al. [22] applied an innovative approach using CNN techniques. Instead of using neural networks to classify their samples, they used CNN techniques for feature extraction and pre-processing, resulting in a better classifier. The method made use of the publicly available dataset from the International Skin Imaging Collaboration (ISIC), which had 900 training samples and 379 test samples. The samples belonged to two classes, benign and malignant. Pre-processing included a conversion to grayscale and a downsampling of the image size. After this, the system utilized AlexNet, implementing binary masking and bounding box methods for feature extraction purposes. LDA techniques were used for feature reduction, after which 4 different classifiers and different metrics were used, of which KNN provided the best precision (86%) and the best specificity (99.9%).

Vipin et al. [23] implemented a system that operated in two stages, segmentation and classification. The main driver for developing such a system was to eliminate human interference in the diagnosis of melanoma to make the process less error-prone and less time-consuming. The system utilized an ISIC dataset of 13,000 images, which was reduced to 7,353 images after removing non-usable images. In the segmentation stage, the symmetric U-Net was utilized that comprised 3 main components: Contracting/Downsampling path, Bottleneck, and Expanding/Upsampling path. Each of these components utilizes convolutional layers and maximum pooling layers. A deep residual network was used to train the classification stage model. This network employs CNN and recurrent neural network techniques. Using weighted binary cross-entropy as the loss function, an accuracy of 88.7% with a recall of 91% were obtained.

Nasr-Esfahani et al. [24] devised their own CNN to preprocess, extract features and perform classification. They used a dataset of 170 non-dermoscopic images from the digital image archive of the Department of Dermatology of University Medical Center Groningen (UMCG). The dataset was augmented and consisted of 6,120 original and synthesized images for better training. For preprocessing, illumination correction, mask generation, and Gaussian filter techniques were applied. The CNN itself consisted of an input layer, followed by two layers of convolution and max-pooling, each arranged in an alternate manner and a final fully connected layer. The results were classified into 2 classes, melanoma and nevus. The proposed model provided an accuracy of 81% with a specificity of 80%.

Attia et al. [25] used a fully CNN with autoencoder-decoder architectures such as FCN and SegNet. The proposed architecture encodes input images using 7 convolutional layers with 2 maximum-pooling layers. This was further coupled with a recurrent neural network and Long-Short Term Memory architecture to enhance the output. This model was trained using 900 lesion images and tested on 375 test images, all taken from the ISBI 2016 challenge 'Skin lesion analysis Toward Melanoma Detection'. The proposed model achieved an accuracy of 98% with a specificity of 94%.

Mukherjee et al. [26] developed a CNN Malignant Lesion Detection (CMLD) architecture. This model consists of an input layer, three two-dimensional (2D) convolutional layers separated by two max-pooling layers between them, and a fully connected layer at the very end followed by a soft-max layer for prediction. Two datasets were combined: MEDNODE (1,700 images) and Dermofit (13,000 images). Accuracies of 90.14% and 90.58% were achieved in both datasets individually. After combining the datasets, an accuracy of 83.07% was obtained. The individual results of both models are higher than those obtained with traditional feature-based classification models and other works in the related literature.

Sanketh et al. [27] proposed their own CNN formed by employing 2 convolutional layers and 2 max pool layers and a final fully connected layer. The main objective of this model was to detect skin cancer in the early stages to initiate effective treatment and reduce the mortality rate. The dataset used was obtained from ISIC and consisted of a total of 2,719 images belonging to two categories, benign and malignant. This was further divided into 1,906 training images and 816 testing images. Several different parameters were established and different values were used for them before obtaining an optimal result of 98%.

Rahi et al. [21] proposed a CNN model with Convolutional layers of two different strides. These were combined with max-pooling layers in different combinations to form a total of 9 layers between the input layer and the fully connected layer. The use of dropout layers has also been incorporated to increase the results. The dataset consisting of 2,967 images belonging to two categories – benign and malignant. These were divided into training images (1,440 benign and 1,197 malignant) and 360 test images (360 benign and 300 malignant). The proposed model delivered an accuracy of 84.76% with a specificity of 78.81%.

Gulati et al. [28] employed the use of pretrained networks namely, AlexNet and VGG16, in two different ways, one as a transfer learning paradigm and the other as a feature extractor. The dataset used is PH2, acquired from the Dermatology Service of Hospital Pedro Hispano, Portugal. It consists of 200 images, of which 160 belong to the benign category and 40 belong to the malignant category. The aforementioned networks require inputs of different sizes; hence, the necessary preprocessing was performed. Both AlexNet and VGG16 were used individually for transfer learning and feature extraction. Of these methods, VGG16 provided the best results as a transfer learning model. It delivered an accuracy of 97.5% and a specificity of 96.87%.

Daghrir et al. [12] proposed a hybrid method, combining a convolutional neural network with two classical machine learning techniques, KNN and SVM. A dataset consisting of 640 images of lesions was obtained from the International Skin Imaging Collaboration (ISIC) archive. Of these, 512 images were used for training, while the remaining 128 images were utilized for testing. The CNN architecture consisted of 9 layers in total after the input layer: 3 convolutional layers, 3 max pooling layers, 2 dropout layers, and the final fully connected layer for prediction. Various preprocessing techniques including the Otsu method, filters, the morphological snakes method were applied. The final classification was performed on all three algorithms before the majority vote (88.4% accuracy), in which CNN provided the best individual accuracy at 85.5% and SVM the second best at 71.8%.

Acosta et al. [29] incorporated a mask-based and region-based CNN technique combined with a pretrained ResNet152 structure. The dataset used was taken from the International Symposium on Biomedical Imaging 2017 challenge, and the results were compared to those provided by the models used in the ISIC 2017 challenge. The architecture was implemented in two stages. In the first stage, Mask RCNN was used to create a boundary box on the lesion and in the second stage ResNet152

Table 1 Current methods, datasets, and results of skin cancer classification using CNN

Reference	Methods	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)
[31]	DCNN	PH2	95.00	93.00	95.00
		ISIC 2017	95.00	97.00	96.00
[28]	AlexNet, VGG16	PH2	97.50	100	96.87
[32]	FCNs based on VGG16 and GoogleNet	ISBI 2016	88.92	69.33	93.75
[33]	Deep RCNN and Fuzzy C-Mean Clustering	ISBI 2016	94.20	95.00	94.00
[34]	DenseNet with IcNR	ISBI 2017	93.40	93.00	–
[35]	Optimized CNN	DermIS + Dermquest	93.00	99.40	94.00
[35]	Transfer learning and pre-trained deep neural net	MED-NODE	97.70	97.30	97.40
[36]	Ensemble–ResNet and Inception V3	ISBI 2018	89.00	86.20	79.60
[22]	LDA with CNN	ISBI 2017	85.80	52.00	97.40
[37]	CNN and Novel Regularizer	ISIC Archive	97.49	94.30	93.60

was used to classify this lesion into benign or malignant categories. The proposed model, eVida M6, provided a precision of 90.4% and a specificity of 92.5%, which was an increase of 3.66% precision from the best-performing models of ISIC 2017.

Rahi et al. [21] proposed a CNN network using Keras Sequential API and compared the results they obtained with pre-trained models such as VGG16, RESNET50, and DENSENET121. The dataset used was taken from the ISIC archive and is called 'HAM10000' which consists of 10,015 images. A 6-layer CNN model was proposed consisting of 4 convolutional layers combined with 2 max pooling layers and a final fully connected layer for prediction. The model achieved a precision of 79%. The same dataset was then used with VGG16, RESNET50, and DENSENET50, out of which DENSENET50 provided the best accuracy of 90%.

As a loss function, Patil et al. [30] presented a convolutional neural network with similarity measure for text processing (SMTP). The suggested model was tested on 250 photos of melanoma cancer, with 167 melanomas measuring less than 0.76 mm, 54 melanomas measuring between 0.76 mm and 1.5 mm, and 29 melanomas measuring more than 1.5 mm. Eighty-one characteristics were recovered from the photos after extraction of features. The input, convolutional, rectified linear unit (ReLU), pooling, ReLU Fully Connected, SoftMax Fully Connected, and Loss Function layers make up the architecture. The proposed model had a 96% accuracy and a 96% specificity (Table 1).

CNNs can offer better results than traditional machine learning techniques. This is simply because CNNs have multiple layers, and each layer multiplies the learning capacity of the architecture. In addition, CNNs, unlike traditional algorithms or even simple feedforward networks, do not break the image down into a single column vector. Instead, the pixel stacking is kept intact, although the dimensions may be changed. This helps retain spatial information, which is not the case for other traditional techniques. This allows superior feature extraction and overall better performance, which is a very important factor when classifying lesions or tumors, as every little detail is essential. Although traditional techniques may be typically limited to classification or minor feature extraction tasks, CNNs are highly flexible given the different filters and layers that can be incorporated into an architecture. This allows for building a more custom architecture suited to the type of images or dataset available. Hence, CNNs provide better performance while also allowing a more custom and flexible approach that can be fine-tuned to individual requirements.

3. Support vector machines in skin cancer detection

SVMs are the most powerful algorithms to be developed to date. They are a part of the supervised machine learning techniques with an emphasis on classifying datasets into insightful groups. They are built on

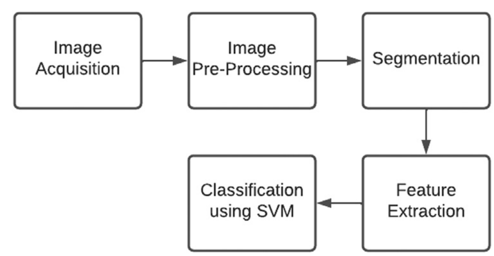

Figure 2. Block diagram for skin cancer classification using SVM.

the concepts of decision planes and decision boundaries. SVMs aim to obtain an optimal hyperplane that maximizes the distance between the closest point of the respective data groups [38]. A set of instances near the optimal hyperplane is called a 'Support Vector'. SVM provides a unified framework for categorizing different data via a suitable kernel selection, i.e., various machine learning architectures can be created by using different kernels. The simplest plane of SVM is termed 'linear', which is used when the data is linearly separable. For nonlinear data, SVMs with different kernel functions are used. Kernel functions map low-dimensional data to a higher plane in which the data can be separated linearly [39].

Bioinformatics has been made available using SVMs. In medical image analysis, the SVM classifier, widely used in research with a melanoma dataset and has been reported to deliver promising results. Protein function prediction, gene expression data classification, and cancer detection are some of the applications of a wide plethora of SVMs [40].

Figure 2 represents a brief workflow to detect skin cancer with SVM. The first step is to acquire a large dataset of images and skin lesion parameters. It is followed by several preprocessing steps which include the conversion of images from RGB to grayscale and the reduction of noise by applying several filters (e.g., Median Filter). On the pre-processed images, segmentation is performed which segments it into affected and unaffected regions. Next, several features are extracted. Using these characteristics, the SVM is trained to classify each unseen skin lesion as benign or malignant.

Doukas et al. [41] designed an innovative mobile system that allowed saving collected skin photographs, drawing out a region of interest, and self-evaluating the images. Based on their severity, the system can detect moles in dermoscopic images and categorize them into benign, dysplastic, and malignant. The method used a dataset of approximately 3,000 photos of skin lesions that had been manually classified. The system was implemented using 11 different classifiers, of which the SVM delivered the best performance with an average accuracy of 77.06%, followed by the Multilayer Perceptron (75.15%).

Mustafa and Kimura [42] presented an automated approach to detect skin cancer from melanoma in photos of afflicted areas of the skin with the aim of achieving greater precision while using only a small set of features. They segmented the images into lesions of interest and extracted 15 features using image processing and computer vision tactics. The system was implemented using a nonlinear SVM with a Gaussian radial basis function (RBF) kernel. The study used 200 photos and it was shown that only six criteria were adequate for the identification of melanoma, according to the test findings. An accuracy of 86.67% was achieved using the best parameters.

Waheed et al. [43] presented a machine learning approach to detect melanoma from dermoscopic images. The study involved extracting color and texture characteristics based on melanoma lesions with distinct structures and varying intensities. They extracted a 13-dimensional feature vector with 9 color and 4 texture features, respectively. Using three-fold cross-validation, the dataset was split into training and testing sets. An SVM classifier was used to categorize melanoma images from all the dermoscopic images in the dataset. Using both color and texture parameters, the model obtained the highest accuracy of 96%.

Babu et al. [44] proposed an efficient system to detect melanoma skin cancer using Histogram of Gradient (HOG) features. The study used the ISIC 2018 dataset, which included 10,015 photos of seven different forms of skin cancer. The initial steps included image preprocessing; resampling followed by feature extraction using HOG. An SVM with an RBF kernel is processed over the features to map them into seven different class labels. The average accuracy achieved by the system based on HOG based feature extraction was 76%, which was greater than the accuracy achieved using SVM alone (67%). In addition, the proposed method was compared to various classification techniques like Random forest (RF), KNN, and Greedy Fusion, which failed to outperform the former approach.

Yuan et al. [45] developed a decision-based support system to aid in the early diagnosis of skin cancer. The primary objective of the system was to utilize the texture information exclusively to predict whether the skin lesions were benign or malignant. They used a three-layer system implicit in SVMs to improve generalization error rates and computational efficiency. To validate the approach, a binary class benchmark classifier was utilized. An SVM with a polynomial kernel of varying degrees was trained on 2000 samples. When identifying the malignancy in skin injury images, an optimal degree 4 polynomial was obtained, resulting in a standard accuracy rate of 70%.

Ilkin et al. [46] proposed a potent approach to detect melanoma using a hybrid classification algorithm. The study was tested with 1,000 images from the ISIC dataset and 200 images from the PH2 dataset. The bacterial colony algorithm, a heuristic optimization algorithm, was used to improve the SVM RBF kernel to obtain a hybrid classification algorithm termed 'hybSVM'. Nine features were derived from segmented images using the ABCDE rule for melanoma detection. The hybSVM algorithm operates in two phases to obtain the optimum gamma and C values. To illustrate the efficacy of the suggested approach, the results were compared using two distinct SVM software toolkits, Scikit-learn and ThunderSVM. The classification using hybSVM achieved an accuracy of 97.56% in the ISIC dataset and 97.50% in the PH2 dataset, which transcended the accuracy of ThunderSVM and Scikit-learn. The results indicated that hybSVM was an effective technique with positive performance results, a reduced time consumption, which could make the dermatologist's diagnostic procedures more convenient.

Murugan et al. [47] proposed a model that identified lesions from dermoscopic images and detected skin diseases. They applied a median filter to eliminate the noise in the images of the ISIC dataset, followed by Mean Shift Segmentation to separate the ROI from the images. Features were extracted using GLCM, Moment Invariants, and GLRLM methods. SVM, RF, Probabilistic Neural Network, and a combination of SVM and RF classifiers were used for the lesion classification. The SVM+RF classifier achieved the highest sensitivity, specificity, and accuracy among all the tested classifiers. An accuracy of 86.12% was obtained for the GLRLM feature, 84.63% and 89.31% for Moment Invariant features and the GLCM feature, respectively.

Arora et al. [48] developed a computer-aided detection and diagnostic system to classify lesions into benign or malignant, made possible by the precise feature extraction technique. For the study, 100 images of the PH2 dataset were used. The features were extracted by applying the bag-of-features (BoF) method with the speeded up robust features (SURF) method as a local feature descriptor. Models like linear SVM, Fine tree, linear discriminant, and quadratic SVM were used for the classification process. The proposed Quadratic SVM exhibited an 85.7% accuracy, 100% sensitivity, and 60% specificity, values which were better than other used classifiers. A 3% increase in performance measures was recorded and compared to state-of-the-art methods.

Carrera and Ron-Dominguez [49] designed a CAD system that helped detect skin cancer using dermoscopic images. The system was tested on a subset of 784 images from the ISIC dataset. Twenty-eight features were extracted based on texture, asymmetry, and border quality. The system used both SVM and decision trees to detect the malignancy. For SVM, the kernels used were linear, Gaussian, and polynomial. The performance result was at par with previous studies in terms of accuracy. SVM was found to be a markedly better classifier in terms of sensitivity. A sensitivity as high as 98% was achieved, avoiding many false-negative diagnoses with high precision, and thus is promising.

Alsaeed [50] developed a skin cancer computer aided diagnosis system (SCCAD) based on SVM. Dermoscopic images were acquired from the PH^2 dataset and the digital image archive of the Department of Dermatology of the University Medical Center Groningen (UMCG) databases. Images were segmented using Otsu's threshold method. A total of 20 features were extracted based on texture, color, and shape. SVM and an ensemble method were adopted to build the classification model. The performance of the two models was assessed using a 10-fold cross-validation and confusion matrix. SVM showed an accuracy of 92.6%, outperforming the ensemble (91.1%) and therefore was adopted in SCCAD. Two Human–Computer Interface (HCI) experts performed an informal study to evaluate the SCCAD system. Gautam and Ahmed [51] proposed a decision-based support system to analyze and assess risks in a sample image. The system employed a SVM with a Gaussian RBF that has been optimized via Sequential Minimal Optimization (SMO) to classify benign and malignant lesions. The dataset consisted of 146 images collected from various sources. After initial pre-processing and segmentation to extract the lesion features more accurately, they extracted the features following the ABCDE rule to obtain a feature vector provided as input to the SVM. Sensitivity and specificity curves were derived for different values of k-fold cross-validation. The SVM model was concluded to yield a promising classification result.

Mete et al. [52] suggested an innovative system to classify skin lesions as melanoma, dysplastic nevus, and benign. The system was implemented in two layers. Three binary SVM classifiers: melanoma versus dysplastic nevus, melanoma versus benign, and benign versus dysplastic nevus, were trained from a 112 lesion-dataset divided into three subparts. The LOO classification procedure was adopted to select the best model of the three independently trained SVMs. An SVM with a degree four polynomial kernel gave the best results. The second layer consisted of a novel decision-maker function that makes use of probability memberships from the previous layer. The system achieved 98% specificity, 76% sensitivity, and 85% F-measure accuracy (Table 2).

SVMs have been widely used in the past and continue to attract research interest. This trend can be credited to the inherent efficiency that SVMs provide. In addition, they deal well with high-dimensional datasets and possess high flexibility in modeling diverse data sources. Compared with neural networks, they preclude the need for weights or arbitrary coefficients, making them computationally faster. Furthermore, SVM optimizations culminate in a global extremum, avoiding landing at a local one due to their convex nature. They also provide substantial resistance to overfitting. Furthermore, with the use of appropriate kernels, one can create new machine learning architectures

Table 2 Current methods, datasets, and results of skin cancer classification using SVM

Reference	Methodology	Datasets	Accuracy (%)	Sensitivity (%)	Specificity (%)
[53]	Segmentation using the Watershed Algorithm, GLCM, and ABCD rule for feature extraction	ISIC (1000 images)	89.43 (ABCD) 85.72 (GLCM)	87.68 (GLCM) 91.15 (ABCD)	83.76 (GLCM) 87.71 (ABCD)
[54]	SVM	ISIC (5341 images)	96.90	95.70	90.20
[55]	Normalized Otsu's Segmentation + Hybrid Adaboost–SVM	Various repositories (992 images)	91.70	94.10	88.70
[56]	Feature extraction using GLCM + HOG	ISIC (1000 images)	97.80	75.00	65.00
[57]	GrabCut technique for segmentation	Dermquest (80 images)	80.00	-	55.36
[58]	Estimation maximization for segmentation + GLCM rule	http://www.dermoscopyatlas.com/ (80 images)	–	96.35	94.95
[56]	Watershed Algorithm for segmentation + GLCM rule for feature extraction	PH^2 (200 images)	80.00	–	–
[31]	SVM	250 images	76.00	61.03	77.66

suited to classify non-linearly separable data. A principal disadvantage of SVM is the enormous computational costs when dealing with large datasets, leading to a slow training time. Overall, SVMs are reliable for cancer detection in general, both in terms of accuracy and flexibility, but are not recommended for very large datasets.

4. K-nearest neighbor for skin cancer detection

The K-nearest neighbor is a lazy learning algorithm. It is one of the most basic machine learning algorithms available. It can be applied to both classification and regression. It is quite sensitive to the data provided. This approach has several advantages, and some have a high accuracy, being insensitive to outliers, and make no assumptions about the data. It has various applications and can be utilized for credit rating, loan management, and stock market forecasting. This paper covers its application to classify images of lesion images as benign or malignant [58].

Figure 3 presents a illustrative flowchart of the approach used to classify skin lesions using KNN. The algorithm is as follows:

Step 1 Input the testing data.
Step 2 Identify the parameter K.
Step 3 Calculate the distance between the data that need to be evaluated with the training set.
Step 4 Arrange the distances in ascending order.
Step 5 According to the value of 'K', pair it with the given data.
Step 6 Assign the datapoint to closest class according to the Euclidean distance [59].

The diagram on the right in Figure 3 shows the general method for the detection of skin cancer. It can be split into three stages: preprocessing, feature extraction, and classification. Pre-processing is the first stage which involves removing noise or hair using an image filtering algorithm. The next step is to extract the features (GLCM and color). In the final stage, a classifier is used to determine whether the image is benign or malignant. In this section of the paper, k-nearest neighbor has been used as a classifier. Skin cancer images are taken and given as input to the classifier. This diagram covers a general flow. However, different studies and experiments have different algorithms and methods for pre-processing and feature extraction.

To classify the tumor as malignant, the features of the lesion are recovered by segmentation Shah et al. [60] developed a skin care classification system using a new approach based on texture and color features. This proposed method for tracking skin cancer has been shown to help pathologists determine the type of skin cancer. A benchmark image database of 225 skin cancer images was used to validate the outcomes of the suggested technique. The accuracy achieved using the KNN classifier was 85%, which was the lowest compared to SVM and CNN.

Kavitha et al. [61] proposed an effective system to detect skin cancer in which the features of the text are considered during classification. The malignancy of a tumor is determined by a set of characteristics such as shape and color. For feature selection, a sequential forward selection technique was used. A total of 250 dermoscopic images were used in the experiment. For global and local texture feature extraction, the training set images were trained using GLCM and SURF, which delivered an accuracy of 78.2% and 85.2%, respectively, for KNN classifiers.

The accuracy of the KNN algorithm can be damaged substantially by the presence of noise or irrelevant features, as well as feature scales that are not proportional to their relevance. Features have received much attention to improve classification.

Murugan et al. [53] proposed a skin cancer detection approach based on segmentation and classification. After sending an image to the system, preprocessing was performed using the median filtering approach. The watershed algorithm was used to segment the preprocessed image. The segmented images were then used to extract features using the ABCD rule, the GLCM feature method, and the contour feature. Finally, classification approaches were employed using 3 classifiers, namely KNN, RF, and SVM. Accuracy obtained with the KNN was the least as opposed to SVM and RF approaches.

Ozkan et al. [62] offered a system in which the lesions were classified into three unique groups such as normal, abnormal, and melanoma by different machine learning algorithms. A pre-classification was attempted using three different groups and a decision support system was created, which was developed to ease the decision-making task for medical experts. The objective of this study was to classify skin lesions using the PH2 dataset. Four different classifiers were used, namely KNN, ANN, SVM and decision tree. KNN classified the images into three different groups of which the accuracy for the normal' class was 92.50%, 78.75% for the abnormal 'class', and 67.50% for the 'melanoma' class. The total accuracy for KNN was 82%. SVM, ANN, and DT had higher accuracies than KNN.

Jenitha et al. [14] took pre-processed images from a medical database as input to 3 different machine learning algorithms which were KNN, SVM, and CNN. Classification was done by assigning two classes, cancerous and noncancerous. The dataset consisted of 1000 images of lesions from a medical institute. They divided the data into three parts: training data, testing data and validation data. The accuracy achieved for KNN was 80%.

Murugan et al. [53]. proposed a machine learning method that identified skin cancer and pores based on pictures. For pre-processing, the image was first filtered and then segmented by contour segmentation.

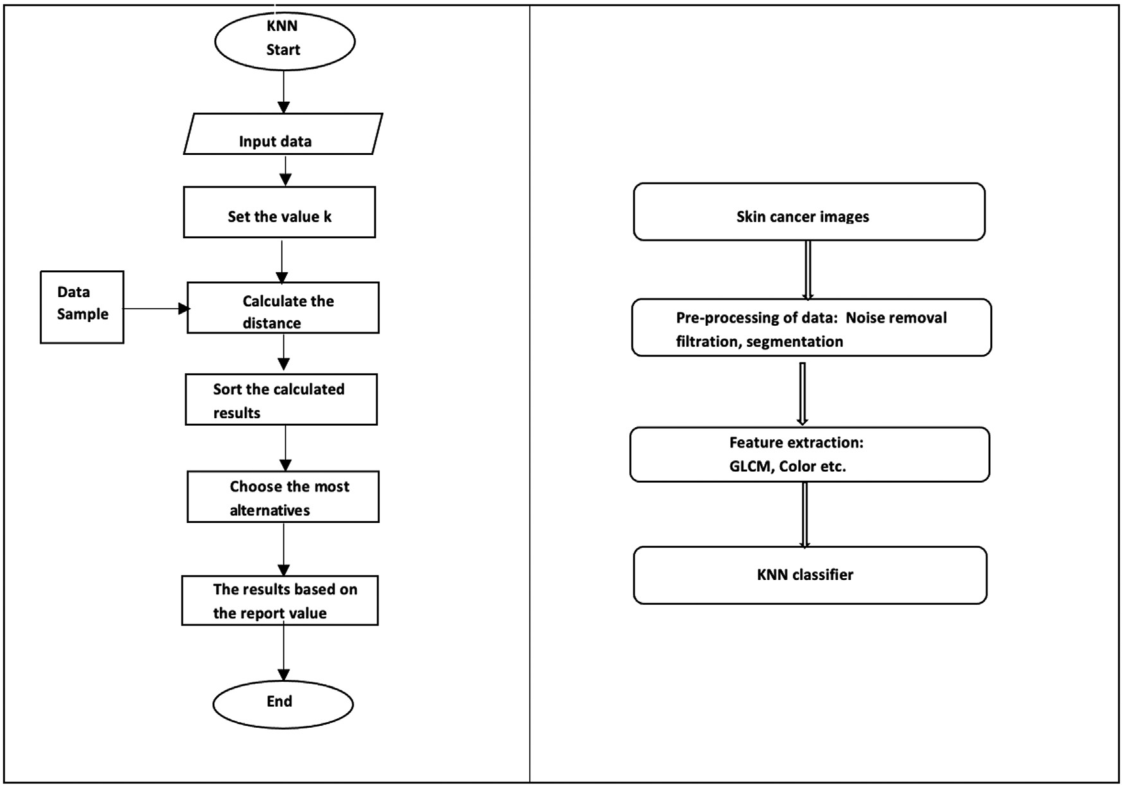

Figure 3. Block diagram for skin cancer classification using KNN.

These images were then fed as input for feature extraction. Feature extraction was done using invariant and GLRM features, after which classification was carried out using one of the classifiers. The two classifiers were used, KNN and SVM. The dataset used was taken from ISIC and consisted of 1,000 images. A 10-fold cross-validation technique was used. An accuracy of 81.77% was obtained for KNN, while the sensitivity was 82.51% and the specificity was 81.04%. The accuracy of KNN was lower than that of SVM.

Lynn et al. [63] proposed a system that was used to alleviate errors caused due to the complex nature of subjectivity and visual interpretation. Initially, the image was made free of unwanted hair as well as noise after which the segmentation process was applied. The mean shift technique was used to extract the characteristics using ABCD dermatological principles. Following this, feature selection was conducted to obtain the most important features. Subsequently, the processed image was fed to the classifiers. The classifiers used were KNN, SVM, and Decision Tree. The dataset used was obtained from ISIC, with 220 images chosen randomly for training and 20 images chosen randomly for testing. For measuring performance, a 5-fold cross-validation was implemented. The accuracy for KNN was the lowest, with 71.4% for the original set of features without any dimension reduction, 66.8% for the original set of features with dimension reduction using PCA, and 76.4% for the selected feature subset via relief without dimension reduction.

Linsangan et al. [64] designed a system in which data preprocessing was performed using a Raspberry Pi device that included segmentation and feature extraction after which the lesion was classified into melanoma, non-melanoma, and unknown classes. The images were obtained from ISIC. A KNN classifier was used and testing was conducted on 15 images. An accuracy of 86.67% was obtained.

Elgamal [65] developed a hybrid technique based on three phases: feature extraction using DWT, feature reduction using PCA, and classification using KNN and ANN classifiers. A computerized clinical decision support system for skin cancer was developed with normal and abnormal classes. The results of the processes were promising, with sensitivity of 100%, specificity of 95%, and accuracy of 97.5% for KNN versus sensitivity of 95%, specificity of 95%, and accuracy of 95% for ANN from a database of 40 photos employed.

Rifi et al. [66] used data acquisition, pre-processing, segmentation, feature extraction, and classification to achieve automatic identification of skin lesion identification. The suggested method was used to analyze skin lesion images from the ISIC datasets, which include 328 benign photos and 672 melanoma photos. Using KNN, the accuracy, sensitivity, and specificity were 95%, 86.2%, and 85%, respectively, second only to SVM whose accuracy was 97.8%. They designed an intelligent decision-making system to classify benign and malignant skin lesions. This approach was used on 100 dermoscopic images and achieves an accuracy of 98.84% using the KNN classifier, as opposed to SVM which gives an accuracy of 56.98% (Table 3).

Although KNNs do not provide results with high accuracy as CNNs and SVMs, they can still be used as a reliable classifier to detect skin cancer. It has been established and repeatedly observed that the accuracy, specificity, and sensitivity of the classifier's performance in detecting cancer are the most important factors to consider, all of which generate lower results for KNN compared to the other two classifiers (Table 4). This is because it demands a large computational runtime with larger sample dataset, which is the runtime of the classifier is commensurate with the sample size. It can also be due to the suboptimal values of k-neighbors being chosen, and hence generating results that are little less than expected. Furthermore, scaling also plays a critical role in obtaining the results. To ensure fair treatment among features, proper scaling must be performed. While there might be a few disadvantages where it falls behind the other two classifiers, it is still a relatively easy and simple machine learning model with fewer hyperparameters to tune. The table below shows the comparison of the advantages and disadvantages of the three algorithms.

Table 3 Current methods, datasets, and results for skin cancer classification using KNN

Reference	Algorithms	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (sensitivity, %)	Dataset
[36]	Mobile net model	92.67	92.66	93.34	92.67	PH2
[67]	Otsu threshold for segmentation	92.70	–	–	93.54	Dataset of 1000 images
[68]	ABCD feature-based method	84.00	87.00	87.00	87.00	DermIS image
[69]	Feature extraction using GLCM and fuzzy mutual information	89.00	86.70	83.70	90.00	Database from the Sydney Melanoma Diagnostic centre, Royal Prince Alfred Hospital.
[63]	Feature extraction using FFT and edge-based features.	98.84	98.92	97.87	1.00	ISIC 2018 database
[70]	Feature extraction using 4 statistical measures (mean, standard deviation, skewness, entropy)	75.88	–	–	68.57	MED-NODE dataset
[64]	ABCD criteria	82.00	80.33	81.45	79.58	PH2 Dataset

Table 4 Advantages and disadvantages of SVM, KNN, and CNN

Machine learning algorithms	Advantages	Disadvantages
SVM	-Works well for high-dimensional places [54].	-Not suitable for large datasets [56].
KNN	-Easy to implement and understand -No explicit training step and all the work happens during prediction [68].	-Difficult to predict the correct value of k -Computationally inefficient [63].
CNN	-Automatic detection of features without any human supervision. -It allows weight sharing [28].	-Large datasets are required [32].

5. Datasets

A brief comparison of the different standard datasets utilized in the studies mentioned in this review, as well as other studies of the same domain, is provided in Table 5. The table shows the total number of images, image classes, and, in some cases, the number of images in the individual training-testing test split. Unlike datasets with only two classes, datasets containing more than two categories can be used for a multi-class classification problem or a binary class classification, depending on the research objective.

6. Challenges and future scope

Melanoma remains an important concern for clinicians and their patients because of its extremely fatal tendency in relatively young individuals. Furthermore, melanomas can easily be mistaken for other benign lesions that are much more prevalent than the former, leading to a misdiagnosis or a delay in the diagnosis of melanoma. Misdiagnosis of melanoma is one of the most common causes of malpractice lawsuits against clinicians. This is one of the biggest challenges faced by healthcare workers and therefore it becomes paramount and necessary to ensure an early and proper diagnosis of melanoma. This can be assisted via the use of different machine learning algorithms such as SVM, CNN, and KNN, each of which with its own set of challenges to ensure the highest accuracy, specificity, and sensitivity. Additional research should be undertaken in the future to assess different algorithms and develop them so that they are more reliable and responsive to specific applications.

Using CNNs, due to the varied availability of datasets, the comparison of results becomes problematic. In the future, researchers will need to use a larger dataset and fine-tune hyperparameters to avoid overfitting. It has been observed that to evaluate their proposed strategies, most researchers did not use standard datasets or employed small samples. Furthermore, CNNs must also train to collect data from individuals with darker skin profiles to achieve greater accuracy. To achieve better results, a variety of age, sex, and races must be included. Conversely, enhancing the accuracy rate is still underway. The objective is to enhance the specificity and overall accuracy of the approaches while maintaining maximum sensitivity.

There are instances where even specialists in computer vision find it difficult to comprehend the inferences made by machine learning frameworks. For example, suppose an algorithm provides an accuracy rate of 80% for diagnosing cancer, it can be puzzling to make sense of why the algorithm makes wrong conclusions about the other 20% of cases. As a result, deep learning algorithms are frequently regarded as a black-box solution that lack a strong justification for their results. They only provide an output in the confidence probability range from 0 to 1. Currently, it is not clear how dermatologists will interpret these results in diagnosing skin cancer.

AI researchers consistently claim that their algorithms outperform dermatologists. However, because these trials were performed in a closed system governed by a number of rules, this picture is far from reality. These performance scores claims are far from the real-life diagnostic setting. Deep learning algorithms are frequently regarded as opaque since their learning is based on the pixel values in image data, and hence lack domain knowledge or the ability to make logical deductions to determine the association between various skin diseases. However, deep learning may be able to do improve diagnosing skin cancer in the future. A well-balanced dataset is crucial for deep learning algorithms to perform well in classification tasks. As a result, balanced datasets with sample cases that fully illustrate the characteristics of a particular skin lesion are necessary and the involvement of qualified dermatologists could be very beneficial in this regard. Since most image datasets consist of skin lesions in people with fair skin, deep learning networks are frequently criticized for social prejudices. To eliminate social or racial discrimination in machine learning models, skin lesion datasets must have racial diversity, that is, the data must consist of skin lesion images from individuals with as many different skin profiles as possible. A similar concern can be extended to age, particularly when factors such as skin aging or solar damage in the surrounding area of the lesions can affect the image data and inadvertently affect learning.

Deep learning architectures such as generative adversarial networks (GAN) are gaining popularity in the medical imaging community. To overcome a limited dataset, GAN is used to produce high-quality synthetic image data that mimics real-life lesion features. The prevalence of each class of skin lesion among patients strongly skews the distribution of skin lesions in publicly available datasets. GAN allows the generation of images of rare or under-represented lesion types such as Merkel cell carcinoma (MCC), Kaposi sarcoma, or sebaceous carcinoma to supplement their shortage in imaging datasets.

Table 5 Brief comparison of the different standard datasets

Datasets	Training	Testing	Total	Classes
ISIC (2016)	900	379	1,279	9: Actinic keratosis, Basal cell carcinoma, Dermatofibroma, Melanoma, Nevus, Seborrheic keratosis, Squamous cell carcinoma, Vascular lesion
ISIC (2018) /HAM10000	10,015	1512	11,527	9: Actinic keratosis, Basal cell carcinoma, Dermatofibroma, Melanoma, Nevus, Seborrheic keratosis, Squamous cell carcinoma, Vascular lesion
MED-NODE / UMCG dataset	Depending on the experiment	Depending on the experiment	170	2: Melanoma (70 images) and Nevus (100 images)
DERMOFIT	Depending on the experiment	Depending on the experiment	1,300	10 – Actinic keratosis (45), Basal cell carcinoma (239), Melanocytic nevus (331), Squamous cell carcinoma (88), Seborrheic keratosis (257), Intraepithelial carcinoma (78), Pyogenic granuloma (24), Hemangioma (96), Dermatofibroma (65), Melanoma (76)
PH2	Depending on the experiment	Depending on the experiment	200	3 – Common nevus (80 images), Atypical nevus (80 images), Melanoma (40 images)

Instead of relying on a single AI solution for the diagnosis of skin cancer, multiple deep learning models can analyze distinct traits or features of skin lesions, make predictions, and generate a definitive conclusion. In this context, cloud computing and storage are becoming more economical, and several models that aim to aid dermatologists in the diagnostic procedures, will be available to be hosted in synchrony around the world. It is common knowledge among AI researchers and clinical professionals that mistakes can affect future decisions.

Technological misdiagnosis should be avoided as much as possible. For this reason, AI solutions are preferred to be used as a background to work on and validate noisy data from real patients to improve their prediction results. This process will take preference until technological systems make enough progress to provide useful information and insight for the diagnosis of skin cancer in professional or remote environments (Tables 1-4).

7. Conclusions

Melanoma skin cancer is a lethal and widespread form of skin cancer, as it is metastasized very quickly. Early detection of melanoma can very likely lead to cure. Both recent and conventional methods have been considered. This review provides a critical and systematic overview of the state-of-the-art machine learning techniques used to determine whether melanoma cells are malignant or benign. The primary focus of this study was to review and analyze different machine learning algorithms used in classifying skin cancer. The following algorithms – SVM, KNN, and CNN provided the best results. These algorithms were implemented on benchmark datasets such as PH2, MEDNODE, Dermofit, Dermquest and others compiled from the archives of the ISIC, ISBI, and other sources. The paper analyzed the shortcomings and advantages of each algorithm, namely KNN, SVM, and concluded with CNNs. Deep-learning techniques such as feature extraction models, fully CNN, and pre-trained models provide a better alternative to traditional machine learning techniques by eliminating the need for performing preprocessing steps and also provide better results overall. It is essential to note that all the experimental results are achieved after several steps of fine tuning. Furthermore, it is crucial that the best results achieved from these studies be applicable and scalable in the real world. To do this, information on the hardware, model configurations, and other technical environments must be provided to replicate the results. The paper concludes by describing the current problems faced in this field and the scope for improvement.

Conflicts of interest statement

The authors declare that there are no conflicts of interest.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author contributions

All the authors make substantial contribution in this manuscript. Harsh Bhatt, Vrunda Shah, Krish Shah, and Ruju Shah participated in drafting and writing the main manuscript. All the authors discussed the results and implication on the manuscript at all stages.

Acknowledgments

The authors are grateful to Department of Computer Science, Institute of Technology, Nirma University, Dhirubhai Ambani Institute of Information and Communication Technology, Department of Chemical Engineering School of Energy Technology, Pandit Deendayal Energy University for the permission to publish this research.

References

[1] Calabro Fabio, Sternberg Cora N. Cancer and its Management. BJU Int 2006;97(3):651 –651. doi:10.1111/j.1464-410x.2006.06115_2.x.
[2] Pirnog I, Oprea C. Cutaneous melanoma risk evaluation through digital image processing. Proceedings of 11th international symposium on electronics and telecommunications. Institute of Electrical and Electronics Engineers Inc; 2015. doi:10.1109/ISETC.2014.7010796.
[3] Khan MQ, Hussain A, Rehman SU, et al. Classification of melanoma and nevus in digital images for diagnosis of skin cancer. IEEE Access 2019;7:90132–44. doi:10.1109/ACCESS.2019.2926837.
[4] O'Neill CH, Scoggins CR. Melanoma. J Surg Oncol 2019;120(5):873–81. doi:10.1002/jso.25604.
[5] Dildar M, Akram S, Irfan M, et al. Skin cancer detection: a review using deep learning techniques. Int J Environ Res Public Health 2021;18(10):5479. doi:10.3390/ijerph18105479.

[6] Alquran H, Qasmieh IA, Alqudah AM, et al. The melanoma skin cancer detection and classification using support vector machine. Proceedings of 2017 IEEE Jordan conference on applied electrical engineering and computing technologies. IEEE; 2017. doi:10.1109/AEECT.2017.8257738.

[7] Leiter U, Eigentler T, Garbe C. Epidemiology of skin cancer. Adv Exp Med Biol 2014;810:120–40. doi:10.1007/978-1-4939-0437-2_7.

[8] Shailaja K, Seetharamulu B, Jabbar MA. Machine Learning in Healthcare: A Review. Proceedings of the 2nd international conference on electronics, communication and aerospace technology. ICECA; 2018. doi:10.1109/ICECA.2018.8474918.

[9] Kharya S, Dubey D, Soni S. Predictive machine learning techniques for breast cancer detection. Available from: www.ijcsit.com (Accessed on May 20, 2021).

[10] Bhagyasri M, Bhavanishree PN, Madan KS, et al. Study on machine learning and deep learning methods for cancer detection. J Image Process AI 2018;4.

[11] Zhang N, Cai YX, Wang YY, et al. Skin cancer diagnosis based on optimized convolutional neural network. Artif Intell Med 2020;102:101756. doi:10.1016/j.artmed.2019.101756.

[12] Daghrir J, Tlig L, Bouchouicha M, et al. Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach. Proceedings of 5th international conference on advanced technologies for signal and image processing (ATSIP). IEEE Xplore; 2020. doi:10.1109/ATSIP49331.2020.9231544.

[13] Thaajwer MA, Ishanka UP. Melanoma Skin Cancer Detection Using Image Processing and Machine Learning Techniques. Proceedings of 2nd international conference on advancements in computing (ICAC). IEEE Xplore; 2020. doi:10.1109/ICAC51239.2020.9357309.

[14] Jenitha A, Amrutha G, Kishore KL, et al. Skin Cancer Recognition and Detection Using Machine Learning Algorithm. Proceedings of the Fist International Conference on Advanced Scientific Innovation in Science, Engineering and Technology. ICASISET; 2020. p. 2021. doi:10.4108/eai.16-5-2020.2304046.

[15] Jutzi TB, Krieghoff-Henning EI, Holland-Letz T, et al. Artificial intelligence in skin cancer diagnostics: the patients' perspective. Front Med (Lausanne) 2020;7:233. doi:10.3389/fmed.2020.00233.

[16] ShahinAli Md, SiponMiah Md, Haque Jahurul, et al. An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models. Mach Learn with Appl 2021;5:100036. doi:10.1016/j.mlwa.2021.100036.

[17] Shahin AH, Kamal A, Elattar MA. Deep Ensemble Learning for Skin Lesion Classification from Dermoscopic Images. Proceedings of 9th Cairo international biomedical engineering conference (CIBEC). IEEE; 2019. doi:10.1109/CIBEC.2018.8641815.

[18] Salem C, Azar D, Tokajian S. An Image Processing and Genetic Algorithm-based Approach for the Detection of Melanoma in Patients. Methods Inf Med 2018;57(1):74–80. doi:10.3412/ME17-01-0061.

[19] Chan S, Reddy V, Myers B, et al. Machine learning in dermatology: current applications, opportunities, and limitations. Dermatol Ther (Heidelb) 2020;10(3):365–86. doi:10.1007/s13555-020-00372-0.

[20] Bhadula* S, Sharma S. IoT-based skin monitoring system. IJRTE 2020;8(5):4258–64. doi:10.35940/ijrte.e7009.018520.

[21] MdMI Rahi, Khan FT, Mahtab MT, et al. Detection Of Skin Cancer Using Deep Neural Networks. Proceedings of IEEE Asia-Pacific conference on computer science and data engineering (CSDE). IEEE; 2019. doi:10.1109/CSDE48274.2019.9162400.

[22] Majtner T, Yildirim-Yayilgan S, Hardeberg JY. Optimised deep learning features for improved melanoma detection. Multimed Tools Appl 2018;78(9):11883–903. doi:10.1007/s11042-018-6734-6.

[23] Vipin V, Nath MK, Sreejith V, et al. Detection of Melanoma using Deep Learning Techniques: A Review. Proceedings of 2021 international conference on communication, control and information sciences (ICCISc). IEEE Xplore; 2021. doi:10.1109/ICCISc52257.2021.9484861.

[24] Nasr-Esfahani E, Samavi S, Karimi N, et al. Melanoma detection by analysis of clinical images using convolutional neural network. Proceedings of 38th annual international conference of the IEEE engineering in medicine and biology society (EMBC). IEEE Xplore; 2016. doi:10.1109/EMBC.2016.7590963.

[25] Attia M, Hossny M, Nahavandi S, et al. Skin melanoma segmentation using recurrent and convolutional neural networks. Proceedings of IEEE 14th international symposium on biomedical imaging (ISBI 2017). IEEE Xplore; 2017. doi:10.1109/ISBI.2017.7950522.

[26] Mukherjee S, Malu A, Balamurali AR, et al. TwiSent: a multistage system for analyzing sentiment in twitter. Proceedings of the 21st ACM international conference on Information and knowledge management - CIKM '12. ACM Digital Library; 2012. doi:10.1145/2396761.2398684.

[27] Sanketh RS, Madhu Bala M, Narendra Reddy PV, et al. Melanoma Disease Detection Using Convolutional Neural Networks. Proceedings of 4th international conference on intelligent computing and control systems (ICICCS). IEEE Xplore; 2020. doi:10.1109/ICICCS48265.2020.9121075.

[28] Gulati S, Bhogal RK. Detection of Malignant Melanoma Using Deep Learning. Proceedings of international conference on advances in computing and data sciences. Springer; 2019. p. 312–325.. doi:10.1007/978-981-13-9939-8_28.

[29] Jojoa Acosta MF, Caballero Tovar LY, Garcia-Zapirain MB, et al. Melanoma diagnosis using deep learning techniques on dermatoscopic images. BMC Med Imaging 2021;21(1):6. doi:10.1186/s12880-020-00534-8.

[30] Patil R, Bellary S. Machine learning approach in melanoma cancer stage detection. J King Saud Univ - Comput Inf Sci 2022;34(6):3285–93. doi:10.1016/j.jksuci.2020.09.002.

[31] Adegun AA, Viriri S. Deep learning-based system for automatic melanoma detection. IEEE Access 2020;8:7160–72. doi:10.1109/ACCESS.2019.2962812.

[32] Jayapriya K, Jacob IJ. Hybrid fully convolutional networks-based skin lesion segmentation and melanoma detection using deep feature. Int J Imaging Syst Technol 2019;30(2):348–57. doi:10.1002/ima.22377.

[33] Nida N, Irtaza A, Javed A, et al. Melanoma lesion detection and segmentation using deep region based convolutional neural network and fuzzy C-means clustering. Int J Med Inform 2019;124:37–48. doi:10.1016/j.ijmedinf.2019.01.005.

[34] Khan MA, Sharif M, Akram T, et al. Developed Newton-Raphson based deep features selection framework for skin lesion recognition. Pattern Recognit Lett 2020;129:293–303. doi:10.1016/j.patrec.2019.11.034.

[35] Hosny KM, Kassem MA, Foaud MM. Classification of skin lesions using transfer learning and augmentation with Alex-net. PLoS ONE 2019;14(5):e0217293. doi:10.1371/journal.pone.0217293.

[36] Rodrigues D de A, Ivo RF, Satapathy SC, et al. A new approach for classification skin lesion based on transfer learning, deep learning, and IoT system. Pattern Recognit Lett 2020;136:8–15. doi:10.1016/j.patrec.2020.05.019.

[37] Albahar MA. Skin lesion classification using convolutional neural network with novel regularizer. IEEE Access 2019;7:38306–13. doi:10.1109/ACCESS.2019.2906241.

[38] Battineni G, Sagaro GG, Chinatalapudi N, et al. Applications of machine learning predictive models in the chronic disease diagnosis. J Pers Med 2020;10(2):21. doi:10.3390/jpm10020021.

[39] Cervantes J, Garcia-Lamont F, Rodríguez-Mazahua L, et al. A comprehensive survey on support vector machine classification: applications, challenges and trends. Neurocomputing 2020;408:189–215. doi:10.1016/j.neucom.2019.10.118.

[40] Yang ZR. Biological applications of support vector machines. Brief Bioinform 2004;5(4):328–38. doi:10.1093/bib/5.4.328.

[41] Doukas C, Stagkopoulos P, Kiranoudis CT, et al. Automated skin lesion assessment using mobile technologies and cloud platforms. Proceedings of annual international conference of the IEEE engineering in medicine and biology society. IEEE Xplore; 2012. doi:10.1109/EMBC.2012.6346458.

[42] Mustafa S, Kimura A. A SVM-based diagnosis of melanoma using only useful image features. Proceedings of 2018 international workshop on advanced image technology IWAIT; 2018. p. 1–4. doi:10.1109/IWAIT.2018.8369646.

[43] Mustafa S, Kimura A. An efficient machine learning approach for the detection of melanoma using dermoscopic images. Proceedings of international workshop on advanced image technology (IWAIT). IEEE; 2018. doi:10.1109/C–CODE.2017.7918949.

[44] Neela Krishna Babu G, Joseph Peter V. Skin cancer detection using support vector machine with histogram of oriented gradients features. ICTACT J Soft Comput 2021;11(2):2301–5. doi:10.21917/ijsc.2021.0329.

[45] Yuan X, Yang Z, Zouridakis G, et al. SVM-based texture classification and application to early melanoma detection. Conf Proc IEEE Eng Med Biol Soc 2006;2006:4775–8. doi:10.1109/IEMBS.2006.260056.

[46] İlkin S, Gençtürk TH, Kaya Gülağız F, et al. hybSVM: bacterial colony optimization algorithm based SVM for malignant melanoma detection. Eng Sci Technol an Int 2021;24(5):1059–71. doi:10.1016/j.jestch.2021.02.002.

[47] Murugan A, Nair SAH, Preethi AAP, et al. Diagnosis of skin cancer using machine learning techniques. Microprocess Microsyst 2021;81:103727. doi:10.1016/j.micpro.2020.103727.

[48] Arora G, Dubey AK, Jaffery ZA, et al. Bag of feature and support vector machine based early diagnosis of skin cancer. Neural Comput Appl 2020;34(11):8385–92. doi:10.1007/s00521-020-05212-y.

[49] Carrera EV, Ron-Domínguez D. A computer aided diagnosis system for skin cancer detection. Commun Comput Inf Sci 2018:553–63. doi:10.1007/978-3-030-05532-5_42.

[50] Alamri A, Alsaeed D. On the development of a skin cancer computer aided diagnosis system using support vector machine. Biosci Biotech Res Comm 2019;12(2):297–308. doi:10.21786/bbrc/12.2/12.

[51] Gautam D, Ahmed M. Melanoma detection and classification using SVM based decision support system. Proceedings of annual IEEE India conference (INDICON). IEEE Xplore; 2015. doi:10.1109/INDICON.2015.7443447.

[52] Mete M, Sirakov NM, Griffin J, et al. A novel classification system for dysplastic nevus and malignant melanoma. Proceedings of IEEE international conference on image processing (ICIP). IEEE Xplore; 2016. doi:10.1109/ICIP.2016.7532993.

[53] Murugan A, Nair SAH, Kumar KPS. Detection of skin cancer using SVM, random forest and kNN classifiers. J Med Syst 2019;43(8):269. doi:10.1007/s10916-019-1400-8.

[54] Banasode P, Patil M, Ammanagi N. A melanoma skin cancer detection using machine learning technique: support vector machine. IOP Conf Ser: Mater Sci Eng 2021;1065(1):012039. doi:10.1088/1757-899X/1065/1/012039.

[55] Premaladha J, Ravichandran KS. Novel approaches for diagnosing melanoma skin lesions through supervised and deep learning algorithms. J Med Syst 2016;40(4):96. doi:10.1007/s10916-016-0460-2.

[56] Farooq MA, Azhar MAM, Raza RH. Automatic Lesion Detection System (ALDS) for Skin Cancer Classification Using SVM and Neural Classifiers. Proceedings of IEEE 16th international conference on bioinformatics and bioengineering (BIBE). IEEE; 2016. doi:10.1109/BIBE.2016.53.

[57] Mustafa S, Dauda AB, Dauda M. Image processing and SVM classification for melanoma detection. Proceedings of international conference on computing networking and informatics (ICCNI). IEEE Xplore; 2017. doi:10.1109/ICCNI.2017.8123777.

[58] Vaishnavi KR. Detecting melanoma cancer using image processing. Int J Res Appl Sci Eng Technol 2018;6(5):6–13. doi:10.22214/ijraset.2018.5002.

[59] Lubis Z, Sihombing P, Mawengkang H. Optimization of K Value at the K-NN algorithm in clustering using the expectation maximization algorithm. IOP Conf Ser: Mater Sci Eng 2020;725(1):012133. doi:10.1088/1757-899X/725/1/012133.

[60] Shah VV, Mirani SJ, Nanavati YV, et al. Stock market prediction using artificial neural networks. Int J Soft Comput Eng 2016;6(1). Available from: http://www.ijsce.org/wp-content/uploads/papers/v6i1/A2816036116.pdf .

[61] Kavitha JC, Suruliandi A, Nagarajan D. Melanoma detection in dermoscopic images using global and local feature extraction. IJMUE 2017;12(5):19–28. doi:10.14257/ijmue.2017.12.5.02.
[62] Ozkan IA, Koklu M. Skin lesion classification using machine learning algorithms. Int J Intell Syst Appl Eng 2017;4(5):285–9. doi:10.18201/ijisae.2017534420.
[63] Lynn NC, Kyu ZM. Segmentation and Classification of Skin Cancer Melanoma from Skin Lesion Images. Proceedings of 18th international conference on parallel and distributed computing, applications and technologies (PDCAT). IEEE Xplore; 2017. doi:10.1109/PDCAT.2017.00028.
[64] Linsangan NB, Adtoon JJ. Skin Cancer Detection and Classification for Moles Using K-Nearest Neighbor Algorithm. Proceedings of the 5th international conference on bioinformatics research and applications. ACM Digital Library; 2018. doi:10.1145/3309129.3309141.
[65] Elgamal M. Automatic skin cancer images classification. IJACSA 2013;4(3). doi:10.14569/ijacsa.2013.040342.
[66] Rifi N, Agoulmine N, Chendeb Taher N, et al. Blockchain technology: is it a good candidate for securing iot sensitive medical data? Wirel Commun Mob Comput 2018;2018:1–11. doi:10.1155/2018/9763937.
[67] Victor A, Ghalib M. Automatic detection and classification of skin cancer. Int J Intell Eng Syst 2017;10(3):444–51. doi:10.22266/ijies2017.0630.50.
[68] Araújo RL, Araújo FHD de, Silva RRV e. Automatic segmentation of melanoma skin cancer using transfer learning and fine-tuning. Multimedia Syst 2021;28(4):1239–50. doi:10.1007/S00530-021-00840-3.
[69] Masood A, Al- Jumaily A, Anam K. Self-supervised learning model for skin cancer diagnosis. Proceedings of 7th international IEEE/EMBS conference on neural engineering (NER). 2018; doi:10.1109/NER.2015.7146798.
[70] Shalu, Kamboj A. A Color-Based Approach for Melanoma Skin Cancer Detection. Proceedings of first international conference on secure cyber computing and communication (ICSCCC). 2018; doi:10.1109/ICSCCC.2018.8703309.