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Review on Skin Cancer Detection Using AI

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Abstract

Skin cancer is caused by reasons such as unhealthy life style, air pollution, UV radiation, etc. Various automated machine learning algorithmic solutions have been created in prevalent years to be used to detect such cancers before any major aggravation has taken place. In this paper there is a review on ways can detect disease and alert us before something becomes serious. The goal of this study is to look at how Artificial Intelligence can be used to diagnose skin cancer. With the use of Artificial Intelligence, people can learn what skin illness they have and what safeguards and steps they should take at an early stage, allowing them to treat the disease successfully. Machine learning will be utilized to determine the ailment and assist us in detecting the outcome. Support vector machine is the most prevalently used classification techniques. The findings of this study will aid doctors in treating disease at its onset, preventing future deterioration.

1. Introduction

Skin cancer is a rare and serious disease that should be detected as soon as possible. It can present with a variety of symptoms and come in a variety of forms, all of which can be cured or, thankfully, terminated totally. It can strike anyone of any age group and, if not treated promptly, can be fatal. Skin cancer affects one out of every six persons. It is a disease that affects the body in a variety of ways and causes some body cells to grow fast and uncontrollably, spreading to other parts of the body. Cancer can arise from any of the billions of cells that make up the human body. Overexposure to sunshine has been linked to an increase in sickness, according to medical authorities. Artificial intelligence refers to a robot whose ability to accomplish tasks is controlled by a computer commonly associated with intelligent intelligence and judgement. Artificial Intelligence (AI) for skin cancer detection is a cost-effective and technologically advanced method that can save lives. This paper's work focuses on a review of skin cancer detection that aids in our understanding of the disease and its detection using Machine Intelligence. Python and AI are important parts of the study because they assist us understand how it works and other strategies. The task is divided into three tiers, each of which aids us in comprehending the technique in a clear and accurate manner.

Machine intelligence systems, deep learning algorithms, in particular, are quickly penetrating the medical business. A task to be executed, such as pattern recognition which is automatic, large datasets are analysed using layered mathematical models (1). One of the areas is image analysis where researchers are making the most development right now (2), such as in the qualitative and quantitative analysis of lung nodules on radiographic pictures (3), graphics detection of probable strokes (4), and breast mammograms (5). In the era of dermatology, artificial intelligence or machine learning - based technologies are designed to evaluate the severity of psoriasis or to discriminate among onychomycosis and abundant nails (6, 7). The sensitivities of machine intelligence-based algorithms in distinguishing melanomas from nevi in experimental circumstances were comparable or better than dermatologists' (9–11). Because early evaluation of melanomas improves prognosis and distinguishing melanomas from innocuous lesions is typically difficult, AI-based classification systems could be extremely beneficial to disease struck with worrisome skin lesions. Anyhow, still there is some debate about whether AI can be used for diagnosis in "real-world" healthcare settings. Biases, a lack of transparency and ability to explain the growth, data aggregation and interoperability, stability, security, confidentiality, and ethics of consolidated electronic files are all issues that need to be addressed. (12, 13).

Melanoma as a type of skin cancer can be fatal. Early detection of melanoma enhances the likelihood of survival by 75 percent (14), whereas other kinds of skin cancer have survival rates as low as 4–5%. (15). If these skin lesions are caught early enough, they can be easily treated. Melanoma can swiftly progress to the final stage and cause metastases if discovered late. The patient's probability of surviving are dwindling. Through statistical data, a patient with melanoma in its latter stages can live for up to 5 years. For the early detection of melanoma, the encounter of the experienced dermatologist taking the clinical examinations is quite trivial. The utilisation of pictures produced by dermoscopy devices boosted the finding success rate of skin lesions in clinical examinations. Dermoscopy is a noninvasive technique for assessing the colours and epidermal, dermo epidermal interface, and papillary dermis micro - structural that are not visible to the naked eye in real time. These structures are linked to histological characteristics. Dermoscopy is utilized to magnify visual aspects of lesions that aren't or can't be able to see through normal human eye. Regardless of the existence of such photographs, distinguishing skin lesions with extremely similar characteristics such as shape, texture, edge irregularity, and so on might be challenging. Several analysis techniques are utilised to determine if the lesion is benign or malignant depending on the observed features. To determine the type of lesion, experts employ the ABCD (16) rule, CASH algorithm (17), Menzies method (18), 7-point control list, and 3-point checklist techniques (2008, 2008). Despite the contrasts and advantages of these approaches when compared to one another, pathological exams are the gold standard for the differential diagnosis of skin lesions. It is unnecessary, time-consuming, and costly to request a pathology examination for each patient. It's also a stressful situation for the patient.

Various algorithms and methodologies are being created as a result of advances in artificial intelligence to improve clinical diagnosis success rates. In experiments using Machine learning algorithms have become increasingly popular in past few years, promising findings have been found. When artificial intelligence models and experienced dermatologists were compared in various research, it was discovered that deeper algorithms gave greater benefits in the identification of skin lesions. These techniques may be used to turn any device, substrate, or operating system into a splitting edge medical gadget (21).

The idea of this this article is to give an update on artificial intelligence algorithms for the visitor, the efficacy in detecting skin cancer as well as how to help reduce or minimize or even eradicate it.

2. Types of Skin Cancer

Skin cancer is basically of 2 types. Melanoma and Non-melanoma. Most common type is the non-melanoma in the consensus of fair skin or light-colored skin type.

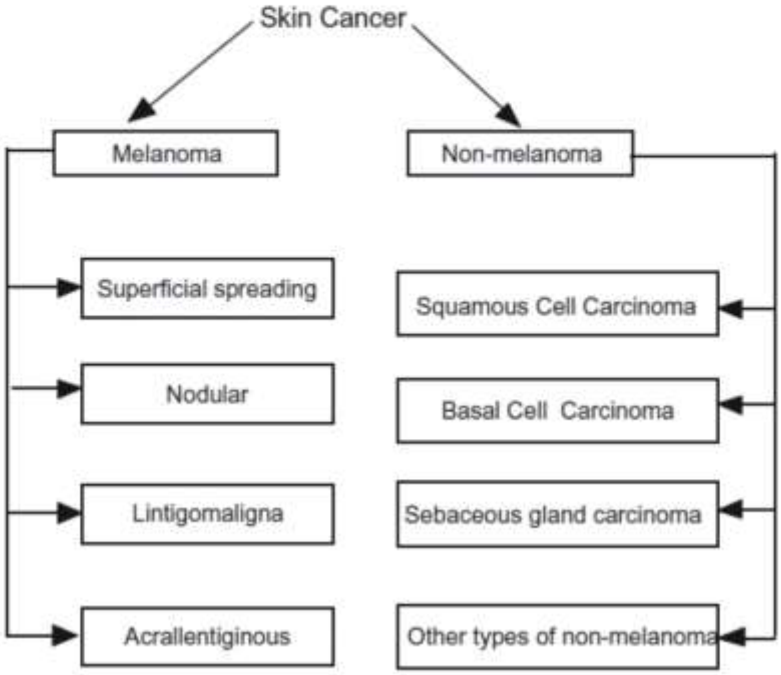

Fig. Skin Cancer type classification

It is again bifurcated ahead into basal cell carcinoma which constitutes 75%, squamous cell carcinoma 24%, and different rare category which is approximately 1% such as sebaceous carcinoma. Melanoma skin cancer is also divided into four categories namely, superficial spreading, nodular, lintigomaligna and acrallentiginous. Apart from this there is a type of cancer called Merkel cell cancer. Merkel cell cancer is not commonly found cancer that is extremely aggressive, or fast-growing. It begins in the hair follicles and hormone-producing cells immediately beneath the epidermis. It's most common in the head and neck area. Merkel cell cancer is also known as cutaneous neuroendocrine carcinoma. Neuroendocrine tumors are a kind of tumor that affects the endocrine system. Individuals with melanoma have a different chance of surviving depending on when they begin therapy. When melanoma is found early on, when it may be surgically removed, the cure rate is quite high. If the melanoma has migrated to other regions of the body, the prognosis is less good.

3. Skin Cancer Detection

Skin cancer, which affects one out of every three people on the planet (22), is a prevalent class of cancer that starts in the epidermal layer of the skin. Exposure to ultraviolet light is one among the many leading causes of skin cancer, accounting for nearly 90 percent of all cases (23). It is one of the fifth most prevalent diseases in an area with a lot of sunshine in the United States (US) in 2018. (24). Melanoma claimed the lives of approximately 2; 490 females and 4; 740 men in 2019 (25) owing to the disease, whilst nearly 20 people die from the disease every day in the United States alone. The top 20 countries' age-standardized melanoma rates are presented in Fig. below, which predicts that a community had a regular age structure, the rate of sickness would be lower. Male patients have a greater chance of getting melanoma than female patients, according to the statistical data shown in the graph below. In 2021, an estimated approximately million additional melanoma cases will be discovered. In 2020, an estimated 6; 850 additional cases of melanoma fatalities are expected, including 4; 610 males and 2; 240 females (26).

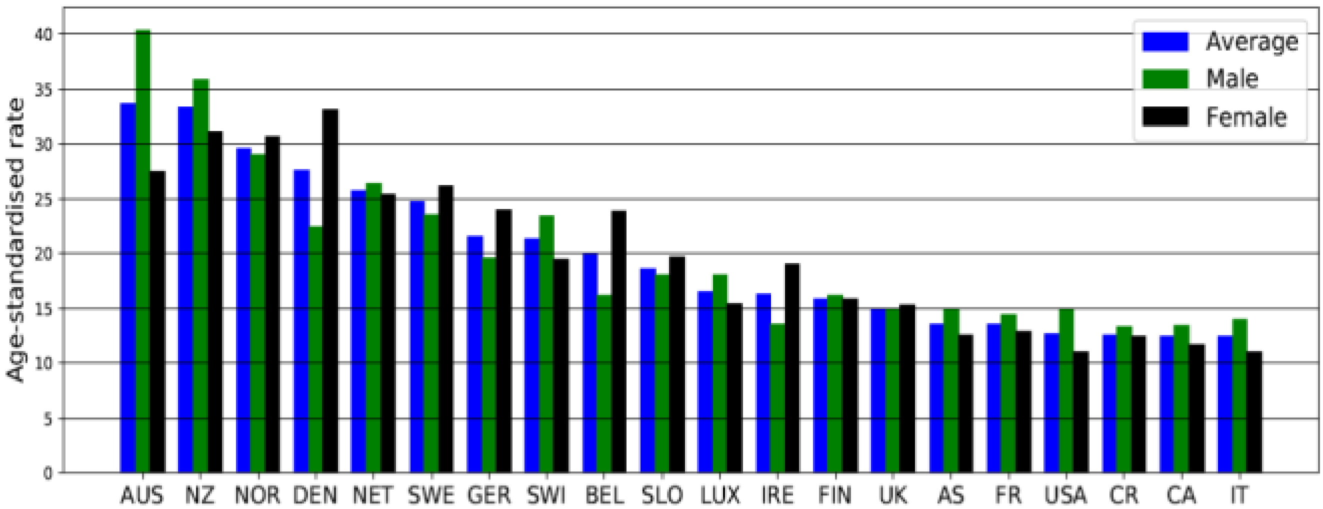

Figure: The top 20 nations with the highest melanoma rates in 2018 according on age-standardized rates per 1:0 million (American Institute for Cancer Research, 2018).

From left to right, the bars represent the nations' declining melanoma cases. Australia (AUS), New Zealand (NZ), Norway (NOR), Denmark (DEN), Netherlands (NET), Sweden (SWE), Germany (GER), Switzerland (SWI), Belgium (BEL), Slovenia (SLO), Luxembourg (LUX), Ireland (IRE), Finland (FIN), United Kingdom (UK) Austria (AS), France (FR), United States of America (USA), Czech Republic (CR), Canada (CA), Italy (IT).

However, a precise and strong early detection is critical in any case, as the mortality rate was reportedly as high as 90% in pre performed recognition. Several imaging techniques are presently being utilized to diagnosis skin cancer, including, optical coherence tomography, ultrasound imaging, confocal scanning laser microscopy and dermoscopic imaging (27). Dermatologists most commonly utilize dermoscopic pictures, also called as epiluminescence light microscopy, to study pigmented skin lesions (28). Because tumors and healthy tissues are so similar, a visual examination with the naked eye might result in a misidentification (29). To address all of the aforementioned constraints and increase the precision of disease prediction, machine diagnosis (CAD) was created. The categorization, for the SLC, this is a stage in a CAD system is an important factor that is hard to conduct due to a variety of objects such as body hair & fibres, air bubbles, markers, shadows, oupas haloing, reactions, on-uniform bright lights, spinning lines, and patient-specific effects such as lesion morphology & color, shape of concentrated lesion area, and patient-specific consequences such as lesion texture & color (30,31), as shown in Figure below.

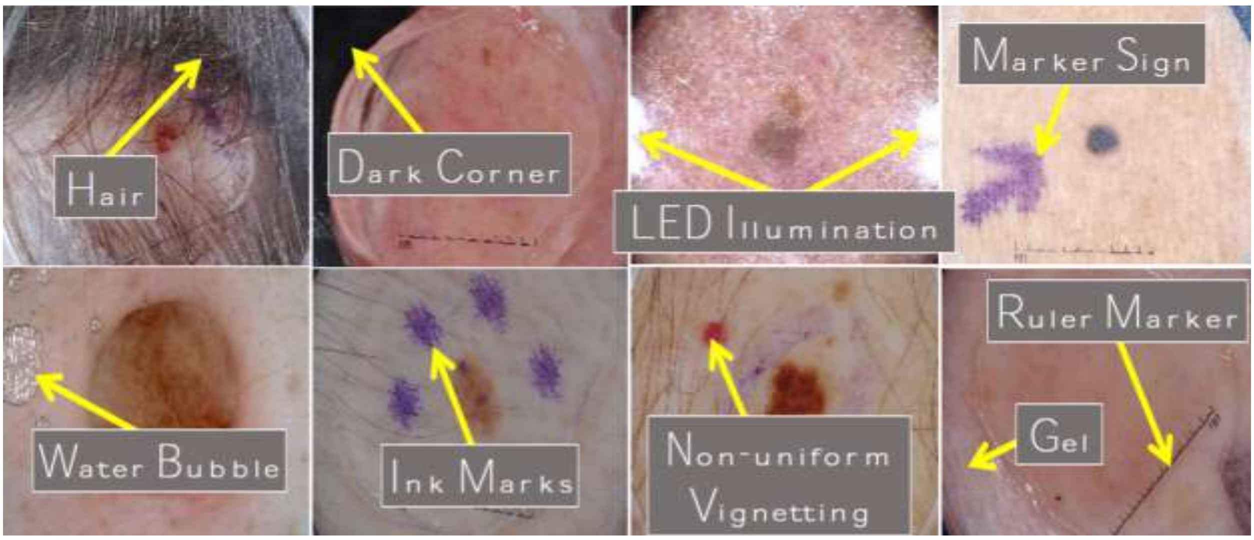

Figure: An example of the challenging dermoscopic images in ISIC dataset with different artifacts

4. Artificial Intelligence in detection of Skin Cancer

Deep learning neural networks are widely used in the detection of skin cancer. It is comprised of a series of inter connected nodes. Its shape and structure is comparable to that of a normal human brain in comparison terms of neuronal connections. Its nodes collaborate to tackle specific issues.

Machine learning neural networks are computer programmers that are programmed to do certain tasks. They function as pro in the areas for what they were programmed. In current research, neural networks were taught and trained and couched to categories images and differentiate of the different skin related cancer cells. International Skin has a variety of skin lesions. For skin cancer detection, we looked into various learning approaches such as ANN, CNN, and KNN. The next sections go over the research on each of these deep neural networks in depth.

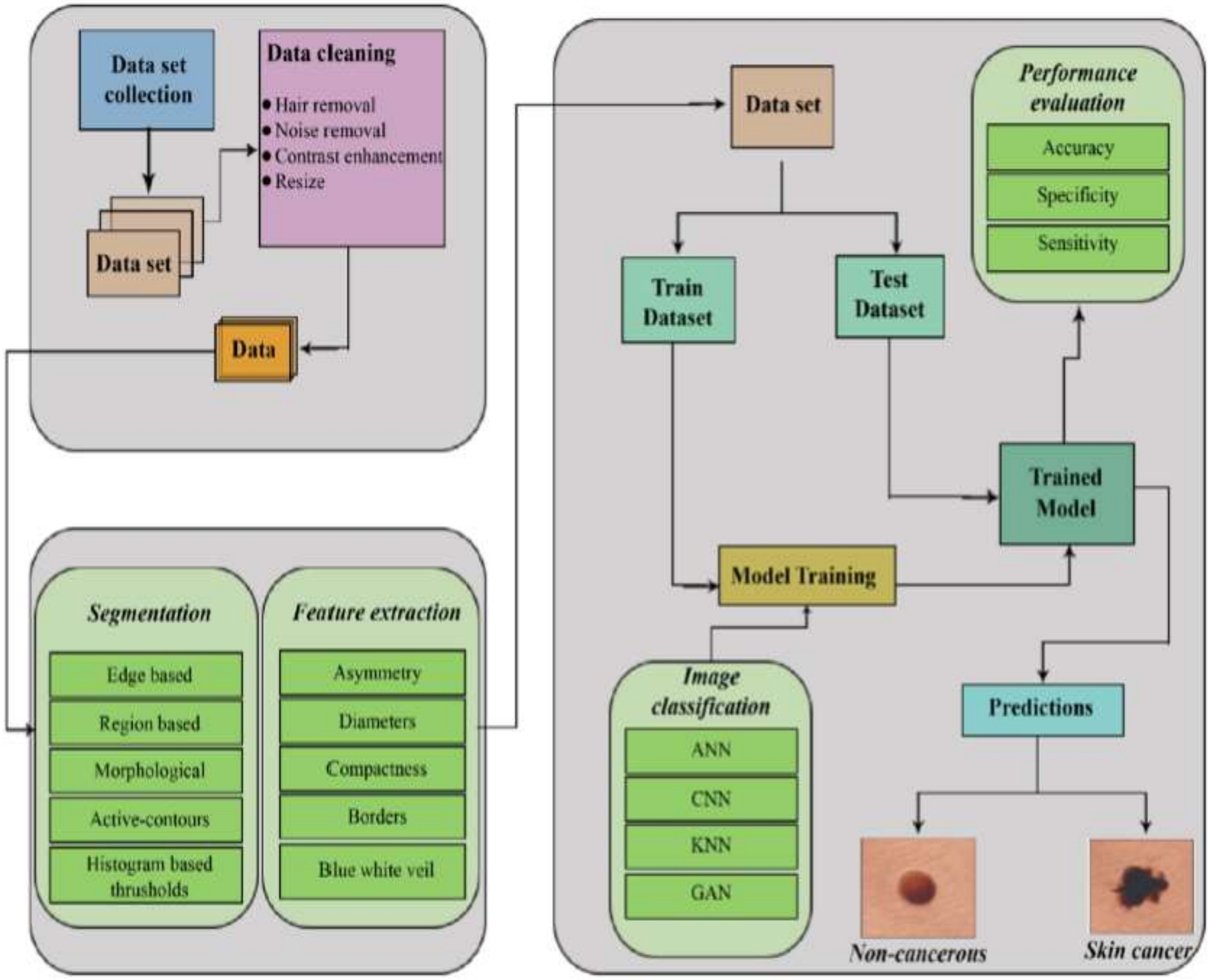

Fig. Skin Cancer Detection Process

I. ANN – Artificial Neural Network
II. CNN – Convolutional Neural Network
III. KNN – Kohonen self-organizing Neural Network
IV. GAN – Generative adversarial Neural Network

I. Artificial Neural Network (ANN)

A statistical and nonlinear prediction approach is an artificial neural network. Its structure is based on the human brain's basic structure. Three layers of neurons make up an ANN. The input layer is the initial layer of neurons, this transmits info to the neurons in the new stage layer of neuron. The hidden layers are the layers in the middle. There may be multiple hidden or undiscovered layers in a traditional ANN. The third layer of output neurons receives data from intermediate neurons. Back propagation is used to learn the complicated associations/relationships between input and output layers, which computations acquire knowledge of at each layer. It works in the same way as a neural network. The terms neural network and artificial neural network appear to be interchangeable in computer science.

In skin cancer detection systems, ANN is employed to differentiate retrieved features. After the training set has been identified as melanoma or non-melanoma, input photos are classified as melanoma as well as non-melanoma skin cancer. The quantity of hidden layers in an ANN is determined by the quantity of images put in the system. The input dataset connects the ANN process's input/first layer to the camouflaged layer. The dataset can be named or unnamed, and either observational or non-regulatory learning mechanisms can be used to handle it. . Back propagation or feed-forward architecture is used by a neural network to learn the weights present at each network connection/link. For the underlying dataset, both architectures use a distinct pattern. Neural networks with a feed-forward architecture only exchange data in a single direction. The data goes from the input to the output.

II. Convolutional Neural Network (CNN)

Convolutional neural networks are the categories of deep neural network widely utilized in computer vision. It's used to classify photos, put together a group of input images, and recognize images. CNN is a terrific technique for gathering and comprehending global and local data by combining salient features like curves and edges to build more complicated features like shapes and corners (32). Convolution layers, nonlinear pooling layers, and fully linked layers are among CNN's hidden layers (33). Multiple convolution layers can be found in a CNN, which are followed by several completely connected layers. Convolution layers, the three main types of layers utilized in CNN are pooling layers, completely connected layers, and full-connected layers (34). CNN-based machine learning systems that are automated and have achieved milestone performance in medical imaging detection, classification operations and segmentation (35). A fully convolutional residual network (FCRN) with 16 residual blocks was employed in the segmentation process to improve efficiency. The recommended approach employs an average of SVM and other classifiers for classification. In melanoma classification, it showed an accuracy of 85.5 percent with segmentation and 82.8 percent without segmentation (36). This suggested a multi-scale CNN. On two density scales of input lesion pictures, the inception v3 framework was fine-tuned: coarse-scale and finer-scale. To capture the shape features of lesions as well as the entire contextual information, the coarse-scale was used. The finer scale, on the other hand, gathered textual information on the lesion in order to differentiate between numerous types of skin lesions.

III. Kohonen Self-Organizing Neural Network (KNN)

A well-known sort of deep network machine learning is the Kohonen organizing itself map. CNNs are trained using unsupervised learning, which means they don't require any developer participation during the acquiring process, and also the desired knowledge about the input data's properties. A KNN is usually made up of two layers. The very first layer is also known as the input layer, while the other layer is known as the competitive layer. Either of these layers are completely interconnected, with all connections occurring between the first- and second-layer dimensions. A KNN may be used to cluster data without understanding the connections between the input data constituents. Another name for it is a self-organizing map. Instead of an output layer, each and every node in the competitor layer plays the role of the output node in KNNs.

A KNN is most commonly used as a dimensionality reducer. It can take high-dimensional data and reduce it to a low-dimensional format, as a 2D plane. As a result, it offers discrete representations of the input dataset. In terms of learning technique, KNNs differ from other forms of NN because they use competitive learning rather than the error-correcting learning discovered in BPN or feed-forward acquiring system. During the mapping of dimensionality from top to bottom, to the topological component of the input data space is preserved by KNN. Preservation refers to the conservation of different position among the data dimensions of space. Variables that are tighter in the input data space are localized closer together, whereas data points that are further away are mapped further apart in this technique, based on the relative distance between them. As a result, for high-dimensional data, a KNN is the optimal technique. Another important aspect of a KNN is its capacity to generalize. Unknown input data can be recognized and organized by the network.

The ability of a KKN to map difficult relationships of data points, including nonlinear correlations, is its most important feature. KNNs are utilized to diagnose skin cancer because of these advantages.

IV. Generative Adversarial Network (GAN)

GANNs are a form of deep neural network (DNN) influenced by zero-sum game theory i.e., a mathematical understanding of a situation in which the benefit that is won by one of two sides is what is lost by the other side (38). GANs are based on the idea that two neural nets compete to assess and capture variation in a database, such as a generator and a discriminator. The generation module utilizes the data dispensing to produce not real data samples in order to deceive the discriminator module. The discriminator module, on the other hand, is intended to differentiate between genuine and fictitious data samples (39). Even during pre-execution or beta phase, both of these neural networks repeat these phases, and their performance increases with each competition. The capacity of a GAN network to produce not genuine samples that are comparable to actual samples using the same data distribution, such as photorealistic images, is one of its main strengths. GANs that can solve a very important difficulty in deep learning include deep convolutional GAN (DCGAN), super-resolution GAN (SRGAN), Vanilla GAN, condition GAN (CGAN), and Laplacian Pyramid GAN (LPGAN). GANs are now being used to successfully diagnose skin cancer.

5. Evaluation Metrics

A classifier assigns each object to a class. This assignment is generally not perfect and objects may be assigned to the wrong class. To evaluate a classifier, the actual class of the objects must be known. To evaluate the classification quality, the class assigned by the classifier is compared with the actual class. This allows the objects to be divided into the following four subsets:

- True positive (TP): the classifier correctly predicts the positive class.
- True negative (TN): the classifier correctly predicts the negative class.
- False positive (FP): the classifier incorrectly predicts the positive class.
- False negative (FN): the classifier incorrectly predicts the negative class.

5.1. Accuracy

Based on the cardinality of these subsets, statistical quantities for the classifier can now be calculated. A common and widely used quantity is accuracy, which is only a reasonable measure if the different classes in the dataset are approximately equally distributed. Accuracy is calculated by

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{3}$$

It specifies the percentage of objects that have been correctly classified.

5.1. Sensitivity

Two other important metrics are sensitivity and specificity, which can be applied even if the different classes are not equally distributed. Sensitivity indicates the ratio of objects correctly classified as positive out of the total number of positive objects contained in the dataset and is calculated by

$$Sensitivity = \frac{(TP)}{(TP+FN)} \tag{4}$$

5.1. Specificity

Specificity indicates the ratio of negative objects correctly classified as negative out of the total number of negative objects contained in the available dataset and is calculated by

$$Specificity = \frac{(TN)}{(TN+FP)} \qquad (4)$$

The output of a binary classifier is interpreted as a probability distribution over the classes. Normally, objects with an output value greater than 0.5 are assigned to the positive class in a binary classifier and objects with an output value less than 0.5 are assigned to the negative class.

An alternative approach is used based on the receiver operating characteristic (ROC). The threshold used for classification systematically varies between 0 and 1, and the sensitivity and specificity are determined for each selected threshold. The ROC curve is calculated by plotting the sensitivity against 1-specificity and can be used to evaluate the classifier. The further the ROC curve deviates from the diagonal, the better the classifier. A suitable overall measure for the curve is the area under the curve (AUC).

6. Discussions

1. Artificial Intelligence-Based Image Classification for Diagnosis of Skin Cancer: Challenges and Opportunities (By: Manu Goyal1, Thomas Knackstedt2, Shaofeng Yan3, and Saeed Hassanpour4)

They discuss advances in computerized image-based AI problem solving for skin cancer detection, as well as possible hurdles with future possibilities to develop these AI based systems to aid dermatologists in skin cancer diagnosis. They came to the conclusion that in the physical world, ethnic identity, epidermis, tresses, and eye color, profession, disorder, medications, already present sun damage, the amount of nevi, and lifestyle habits (such as sunlight exposure, smoking, and intake of alcohol), clinical history, respond effectively to diagnoses, and other knowledge from the affected person's chart must all be considered. But at the other hand, today's deep learning algorithms rely on clinical imaging data. When such algorithms are used to skin lesions or diseases which are not included in the training dataset, they typically lead to a misdiagnosis. The study also looks into the possibilities of creating effective algorithms to help physicians diagnose skin cancer. Computer vision and dermatological associations must collaborate to enhance current AI solutions and increase the diagnostic dependency and correctness of techniques used for skin cancer diagnosis. AI has the ability to revolutionize skin cancer diagnostics, resulting in a more cost-effective, remote-accessible, and more efficient healthcare facilities.

2. Skin Cancer Detection: Using Deep Learning Techniques (By: Mehwish Dildar 1, Shumaila Akram 2, Muhammad Irfan 3 , Hikmat Ullah Khan 4 , Muhammad Ramzan 2,5, Abdur Rehman Mahmood 6, Soliman Ayed Alsaiari 7, Abdul Hakeem M Saeed 8, Mohammed Olaythah Alraddadi and Mater Hussen Mahnashi)

The research presents a thorough examination of machine learning algorithms for early skin cancer diagnosis. The study looked at research articles on skin cancer diagnosis that were published in respectable journals. The discoveries of this research are put together in the form of tools, graphs, tables, methods, and frameworks to help comprehension. The review provides an overview on ANNs, CNNs, KNNs, and RBFNs for lesion image discrimination. The majority of computer - aided diagnostic research keeps focus on identifying if a certain lesion picture is cancerous. When a diseased asks about a specific skin cancer symptom that has appeared on any region of the body, studies aren't always able to offer a clear response. So far, the study has concentrated on the small subject of signal picture categorization.

3. Deep Learning Solutions for Skin Cancer Detection and Diagnosis (By: Hardik Nahata and Satya P. Singh)

The study's objective was to find a skin cancer detection CNN model that can differentiate between different forms of skin cancer and be helpful in finding the cancer in the early stage. The CNN classification model will be developed with Keras and Tensorflow in Python on the backend. Convolutional layers, Drop - outs layers, Pooling layers, and Thick layers, amongst many others, are used to update the parameters, and the model is built and assessed using multiple network topologies. The model will use Transfer Learning techniques to achieve standard developed. The model will be assessed and trained using data from the ISIC competition archives. It also looked into using data augmentation as a preprocessing step to improve the CNN model's differentiation resilience. Inception Resnet, the best model, with an average accuracy of 91 percent.

4. Skin Cancer Detection using Machine Learning Techniques (By: Vidya M. and Dr. Maya V Karki)

Hybrid feature extraction was utilized in this work to identify skin lesions as benign or melanoma. Machine learning techniques are used to detect skin lesions automatically using the ABCD rule, GLCM, and HOG for feature separation and differentiation. For skin lesion segmentation, the GAC approach was suggested. The segmentation resulted in a JA of 0.9 and a DI of 0.82. Color, uniformity, and dimension of skin lesions, skin lesions textures GLCM, and shape, edge of skin lesions HOG were all produced using the ABCD rule. Multiple machine learning and deep learning methods, such as SVM, KNN, and Nave Bayes, were introduced to deal with classification. The proposed approach was tested on ISIC dataset’s skin lesion images. When compared to other classification algorithms, SVM surpasses them with an AC of 97.8% and an AUC of 0.94. Utilizing KNN, the overall sensitivity were 86.2 percent and 85 percent, respectively.

5. Machine Learning in Dermatology: Current Applications, Opportunities, and Limitations (By: Stephanie Chan . Vidhatha Reddy . Bridget Myers . Quinn Thibodeaux . Nicholas Brownstone . Wilson Liao)

The goal of this work was to give a handbook for dermatologists to guide or elucidate the foundations of machine learning and its vast variety of usage so that they could better assess its possible benefits and drawbacks. In dermatology, machine learning has a lot of possibilities, from diagnostics to forecasting more effective and safer therapies. Dermatologists would need to learn how to use this innovation as it develops. How ML works, as well as how and where it can and must be applied in a clinical situation. While machine learning approaches are effective, they are nonetheless similar to earlier clinical tools in that physician evaluation is required for in practice usage. We must also be aware of how hidden biases may impede with the algorithms' black - box testing character. It's also critical to make these technologies accessible to people with different skin tones. Further ML research should be inclusive, with algorithms and datasets made publicly available for validation and testing. Prior to bringing a product to market, it should undergo thorough peer-reviewed randomized clinical trials. Overall, more dermatologists need to be involved in the progression, advancement and testing of ML if the technology is to be helpful and physiologically important.

6. Human–computer collaboration for skin cancer recognition. (By: Philipp Tschandl, Christoph Rinner, Zoe Apalla, Giuseppe Argenziano, Noel Codella, Allan Halpern, Monika Janda, Aimilios Lallas, Caterina Longo, Josep Malvehy, John Paoli, Susana Puig, Cliff Rosendahl, H. Peter Soyer, Iris Zalaudek and Harald Kittler)

The writers and discoverers of this study expand on previous advancements in image-based AI for skin cancer finding accuracy to look at the implications of numerous interpretations of AI-based assistance over a variety of clinical skill levels and health processes. They observed that strong AI-based clinical judgement call support improves diagnostic accuracy more than AI or physicians alone, and that AI-based aid is most beneficial to clinicians with the least experience. They also observed that AI-based more than one class chances over performed CBIR representations of AI in the setting of mobile technology, and that AI-based assistance was beneficial in simulations of second views and telemedicine triage. They also found that AI may deceive a wide range of doctors, including experts, highlighting the potential benefits of high-quality AI through fraudster clinicians.

Table I: A comparative analysis of skin cancer detection using ANN approaches

Ref	**Skin Cancer Diagnoses**	**Classification algorithm**	**Dataset**	**Description**	**Results (%)**
[23]	Melanoma	ANN with Backpropagation	31 dermoscopic images	ABCD parameters for feature extraction	Accuracy = 96.9%
[20]	Melanoma/non Melanoma	ANN with Backpropagation	90 dermoscopic images	maximum entropy for thresholding, and graylevel co-occurrence matrix for features extraction	Accuracy = 86.66%
[19]	Cancerous/noncancerous	ANN with Backpropagation	31 dermoscopic images	2D-wavelet transform for feature extraction and thresholding for segmentation	-
[24]	Malignant/Benign	Feed-forward ANN with the backpropagation training algorithm	326 lesion images	Color and shape features of the tumor were used as discriminant features for classification	Accuracy=80%

[25]	Malignant/Benign	ANN with Backpropagation	448 mixed type images	ROI and SRM for segmentation	Accuracy = 70.4%
[21]	Cancerous/noncancerous	ANN with backpropagation algorithm	30 cancerous/ noncancerous images	RGB color features and GLCM techniques for feature extraction	Accuracy = 86.66
[18]	Common mole/non-common mole/melanoma	Feed-forward BPNN	200 dermoscopic images	Features extracted according to ABCD rule	Accuracy (97.51)
[26]	Cancerous/noncancerous	Artificial neural network with backpropagation algorithm	50 dermoscopic images	GLCM technique for feature extraction	Accuracy (88)
[27]	BCC/non-BCC	ANN	180 skin lesion images	Histogram equalization for contrast enhancement	Reliability (93.33)
[14]	Melanoma/Nonmelanoma	ANN with Levenberg–Marquardt (LM), resilient backpropagation (RBP), and scaled conjugate gradient (GCG) learning algorithms	135 lesion images	Combination of multiple classifiers to avoid the misclassification	Accuracy (SCG:91.9, LM: 95.1, RBP:88.1)
[13]	Malignant/benign	ANN meta-ensemble model consisting of BPN and fuzzy neural network	Caucasian race and xanthous-race datasets	Self-generating neural network was used for lesion extraction	Accuracy (94.17) Sensitivity (95), specificity (93.75)
[38]	Benign/malignant	LightNet (deep learning framework), used for classification	ISIC 2016 dataset	Fewer parameters and well suited for mobile applications	Accuracy (81.6), sensitivity (14.9), specificity (98)
[31]	Melanoma/benign	CNN classifier	170 skin lesion images	Two convolving layers in CNN	Accuracy (81), sensitivity (81), specificity (80)
[36]	BCC/SCC/melanoma/AK	SVM with deep CNN	3753 dermoscopic images	Pertained to deep CNN and AlexNet for features	Accuracy (SCC: 95.1, AK: 98.9, BCC: 94.17)
[39]	Melanoma /benign Keratinocyte carcinomas/benign SK	Deep CNN	ISIC-Dermoscopic Archive	Expert-level performance against 21 certified dermatologists	Accuracy (72.1)
[35]	Malignant melanoma and BC carcinoma	CNN with Res-Net 152 architecture	The first dataset has 170 images the second dataset contains 1300	Augmentor Python library for augmentation.	AUC (melanoma: 96, BCC: 91)

			images		
[40]	Melanoma/nonmelanoma	SVM-trained, with CNN, extracted features	DermIS dataset and DermQuest data	A median filter for noise removal and CNN for feature extraction	Accuracy (93.75)
[41]	Malignant melanoma/nevus/SK	CNN as single neural-net architecture	ISIC 2017 dataset	CNN ensemble of AlexNet, VGGNet, and GoogleNetfor classification	Average AUC:9 84.8), average accuracy (83.8)
[42]	BCC/nonBCC	CNN	40 FF-OCT images	Trained CNN, consisted of 10 layers for features extraction	Accuracy (95.93), sensitivity (95.2), specificity (96.54)
[43]	Cancerous/noncancerous	CNN	1730 skin lesion and background images	Focused on edge detection	Accuracy (86.67)
[37]	Benign/melanoma	VGG-16 and CNN	ISIC dataset	Dataset was trained on three separate learning models	Accuracy (78)
[44]	Benign/malignant	CNN	ISIC database	ABCD symptomatic checklist for feature extraction	Accuracy (89.5)

Conclusion and Future Work

Numerous AI or machine learning strategies for skin cancer identification and bifurcation were discussed in this systematic review research. These methods are all non-invasive. In the diagnosis of skin cancer, preparation and image fragmentation are preceded by careful extraction and categorization. This review concentrates on ANNs, CNNs, KNNs, and RBFNs for lesion image categorization. The most important factor in achieving the best results is choosing the right classification technique. When it comes to identifying picture data, however, CNN outperforms other types of neural networks since it has a stronger connection to computer vision than the others. The majority of skin cancer identification and detection research focuses on identifying if a certain lesion picture is cancerous or not. Existing research, on the other hand, is unable to offer a response when a affected person inquiries about a specific skin cancer symptom that is visible on any part of their body.

The study has so far been limited to the subject of signal picture classification. To find an answer to the topic that frequently occurs, future research could use full-body photography. The image acquisition phase will be automated and sped up with autonomous full-body photography. Auto-organization is a concept that has been created just in the field of deep learning technology. Auto-organization is an unsupervised learning approach for detecting features and discovering relationships or patterns in picture samples in a dataset.

Convolutional machine learning, which include auto-organization techniques, improve the degree of features representation provided by pro systems. Auto-organization is a paradigm that is still under investigation and succession. But in any case, its discoveries may one day aid in improving the accuracy of image processing systems, particularly in the realm of medical imaging, in which the finest details of characteristics are very crucial for correct sickness detection.

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