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A Comprehensive Review on Skin Cancer Detection Strategies using Deep Neural Networks

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Abstract: Skin cancer is a deadly malignancy. Incomplete D.N.A. repair in skin cells causes hereditary mutations and cancer. Early skin cancer is easier to treat since it spreads slowly to other body areas. As a result, the optimal time to find it is during its infancy. Because of the rising frequency of skin cancer, the high mortality rate, and the high cost of medical treatment, early detection of skin cancer symptoms is essential. Researchers have created a variety of early detection techniques for skin cancer due to these obstacles. A lesion's symmetry, coloration, size, and shape help doctors identify and differentiate between skin cancer and melanoma. These considerations prompted the researcher to do research into automated skin cancer diagnosis. The use of machine learning is quickly becoming one of the most promising approaches to the early detection and treatment of skin cancer. A recent study demonstrated the ability of deep network topologies to segment and analyzes skin cancer. According to the findings of this study, further investigation into the application of Deep Learning (DL) algorithms for the early detection of skin cancer is required. An investigation into significant research articles on skin cancer diagnosis that have been published in reputable journals was carried out.

Keywords: Skin Cancer, Segmentation, Deep Networks, Lesion Detection, Classification

Introduction

An alarming increase in the number of cases of skin cancer has been linked to the pollution of the world's air and the depletion of the ozone layer. According to the available information, skin cancer is the most common form of cancer in the general population. Melanoma and non-melanoma are the two types of skin cancer most frequently. Melanoma is one of the most dangerous forms of skin cancer and it is one of the most common. Melanoma accounts for less than one percent of all cases of skin cancer, but it has the highest mortality rate of any skin cancer (Nawaz *et al*., 2022). Melanocytes are responsible for developing melanoma, the most lethal form of skin cancer. Toxic melanocytes can potentially develop into malignant tumors that can affect any organ or tissue in the body. The hands, face, neck, lips, and other sun-exposed areas are typical locations for its appearance. If not caught early, melanoma cancer will spread to other areas of the body and the patient will pass away in excruciating pain (Dildar *et al*., 2021). Non-melanoma malignancies include basal cell carcinoma, squamous cell carcinoma, and sebaceous gland carcinoma. It is highly improbable that these cancer cells will spread to any other body organs.

Treating cancers that are not melanoma is more difficult (Adegun and Viriri, 2021). As a consequence of this, the identification of skin cancer at an early stage is essential for effective treatment (Lakshminarayanan *et al*., 2022). Doctors typically use the procedure known as a biopsy to diagnose cases of skin cancer. A biopsy of the lesion is required to determine whether or not a suspicious skin lesion is cancerous. The manual process is challenging, time-consuming, and inefficient all at the same time. Indications of skin cancer can now be diagnosed more expediently, at a lower cost, and in a shorter amount of time, all thanks to computer-based technology. A variety of non-invasive procedures can be used to determine whether or not the symptoms of skin cancer are brought on by melanoma. Image capture, preprocessing, segmentation, feature extraction, and selection and classification are all depicted in Fig. 1 (Mane and Shinde, 2017), which outlines the processes that must be completed to diagnose skin cancer.

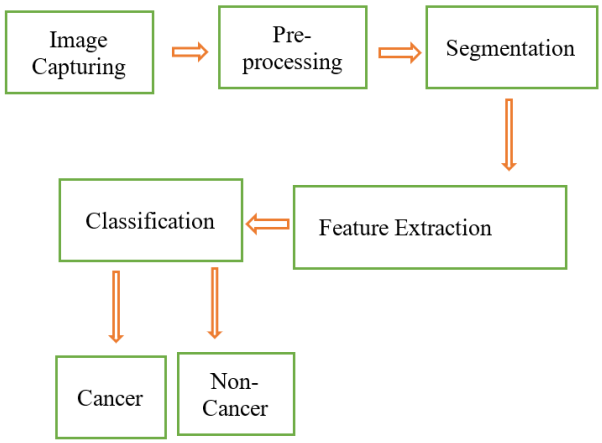

Fig. 1: The conventional flow of the machine learning paradigm

Pre-Processing

The raw data may contain noise and detection algorithms necessitate preprocessing. Noises such as uneven illumination, skin surface light reflection, and hair are commonly seen in skin lesion photographs. Such noises may have an unfavorable impact on segmentation performance and must be addressed. It is possible to reduce noises such as salt and pepper and Gaussian speckle noise using preprocessing techniques such as the wiener and median filters. Skin lesions may be misclassified due to surrounding noise, such as hair. To remove or alter noises, localization, hair removal, image smoothing, color correction, and contrast adjustment should be used in image preprocessing. Using the right preprocessing can help you get better results

Segmentation

Automating the identification of melanoma begins with segmenting the lesion. This phase is the easiest to comprehend but also the most important because the skin lesions' segmentation impacts clinical features and the production of classification features. Separating the backdrop from the lesion and other artifacts is the goal of this phase. The separation is often a binary image, with labels for the excised background skin and the lesion location. Clinical features would be segmented when the lesion site was separated from the backdrop. Border irregularity and asymmetry information would be revealed due to the segmentation. When the background is completely removed, segmentation is regarded as successful.

On the other hand, a less effective segmentation could leave background pixels in the region where the lesion is segmented, especially towards the boundaries. This artifact might negatively impact because it would result in erroneous local and global boundary features and the extraction of color features that would be useless in the subsequent feature segmentation step. Researchers have proposed various strategies for achieving lesion segmentation, an image segmentation task.

Feature Extraction and Selection

Extracting characteristics is the most crucial step in constructing a good classification system. A skin lesion image is retrieved during this step. The image data describes the lesion, successfully classifying whether or not the tumor is malignant. In recent years, substantial progress in computer vision has been made. Researchers using deep learning have extracted more features from various layers.

Classification

Machine learning technologies, profound learning-based algorithms, have demonstrated a greater tendency for usage in medical imaging research, with positive outcomes associated with their application. Once a deep convolution algorithm has been effectively trained, it can improve accuracy, become more objective-oriented and deliver reproducible results. As a result, this review gives an overview of current skin cancer classification techniques. During the last two decades, deep learning has revolutionized machine learning. Artificial Neural Networks (ANNs) are the most advanced branch of machine learning. Deep learning techniques are used in a variety of applications, including speech recognition (Liang and Yan, 2022), pattern recognition (Gray, 2022), and bioinformatics (Yi *et al*., 2022). Deep learning systems have outperformed more standard machine learning methods in various fields. Physicians can detect melanoma early using computational approaches and developments in machine learning, saving money by avoiding costly melanoma diagnoses and unnecessary biopsies. Automatic melanoma detection saves time, money, and effort. Several deep learning algorithms for skin cancer diagnosis have been studied. This study thoroughly evaluates deep learning-based Skin Cancer Detection (S.C.D.) algorithms. We are analyzing traditional deep learning algorithms for the detection of skin cancer. On this subject, a substantial quantity of research has been conducted. As a result, obtaining and interpreting information, classifying it, and summarizing the current study's findings are critical.

ML Algorithms for S.C.D.

In many cases, skin cancers require immediate detection and continued monitoring because of their high prevalence. Patient self-monitoring and decision assistance tools can help less experienced doctors lessen the demand for expert medical services. There are no outside influences on a machine's diagnosis. On the other hand, human diagnosis is prone to individual variation and can be impacted by external circumstances. Skin cancer biopsies could be reduced if Artificial Intelligence (A.I.) is used in this area. Skin cancer patients and their

caregivers can conduct self-examinations once they have completed a training program. As teledermoscopy gains popularity, fewer patients require medical consultation (Kayhomayoon *et al*., 2022). Smartphone apps with A.I. can educate individuals on how to perform a skin inspection and report the results to a doctor. Each type of skin lesion is classed as "benign," "malignant," or "naevi" to develop a new ML skin cancer algorithm. The algorithms are taught on several images before being tested on one and this approach has three elements. 'Ground truth' labels photographs of macroscopic or dermoscopic objects supplied into the algorithm in the first stage. Convolutional layers extract the feature map from the images in the second stage. Data can be represented in a variety of ways in a feature map. Skin lesion patterns can be identified using the machine learning process's feature maps from stage 2. With this update, the DL algorithm can now classify an entirely new image (Malik *et al*., 2022).

According to Alquran *et al*. (2017), an OTSU Thresholding-based skin cancer detection approach has been presented. It was then used to extract characteristics such as ABCD (Atypical, Border, Color, and Diameter), T.D.S., etc. They were correctly categorized using the SVM classifier and RBF Kernel approach with a 92.1 percent accuracy. Ansari and Sarode (2017) developed an image processing technique to detect skin cancer. For lesion segmentation, maximum entropy thresholding was used following preprocessing and extraction of texture features. They could accurately classify 95% of the data using an SVM classifier.

A skin cancer detection and classification system developed by Khan *et al*. (2018) was designed utilizing the normal distribution for picture segmentation. Features are extracted using a histogram of gradients method and entropy-driven feature selection is used for dimensionality reduction. Before deciding on a multi-class SVM classifier, they tried out a variety of other classifiers. These researchers correctly classified 97.5% of the PH2, ISIC, ISBI-2016, and ISBI-2017 datasets.

Vijayalakshmi (2019) used image processing and artificial intelligence to diagnose skin cancer. She used the open-source ISIC dataset to draw 1000-1500 images. After preprocessing, it was possible to segment the lesions using a combination of the Otsu and watershed segmentation methods. It was tested using backpropagation, SVM, and CNN algorithms. The SVM classifier achieved 86% accuracy. Dalila *et al*. (2017) used an Ant-Colony-based segmentation algorithm to categorize melanoma and benign skin lesions. Retrievals were made of properties including shape, texture, and color. Classification accuracy for K.N.N. and ANN classifiers was 85 and 93%, respectively.

Sumithra *et al*. (2015) used region-growing segmentation algorithms to construct a skin cancer diagnostic system. After preprocessing and segmenting the image, these features were extracted. K.N.N., SVM, and a combination of SVM and K.N.N. were used in the final classification stage, with a classification accuracy of 86, 87.5, and 94%, respectively. Most of the scientists depended on their hospital data. Machine learning training can't be done correctly because the dataset is too small for this purpose.

Datasets

Dermatologists, in particular, use clinical and dermatoscopic pictures to monitor the progression of skin diseases. Algorithms can now access vast volumes of data, such as in hospitals, which will allow CNNs to continue to improve in the future. Researchers already have access to data sets. The ISIC archive gallery (Tschandl *et al*., 2018; Nugroho *et al*., 2019) has clinical and dermoscopic skin lesion datasets (e.g., HAM10000 and BCN20000). Two hundred seventy melanomas and 49 seborrheic keratoses are included in an interactive atlas of 1000 clinical examples. Each sample has two images: A dermoscopic image and a close-up image. It is intended for educational use and costs €250 (Combalia *et al*., 2019; Argenziano *et al*., 2000). Images of skin lesions into eleven categories in the Dermofit Image Library. Licensing agreements are required because of the one-time payment and academic licenses providedby DERMOFIT (2021).PH2 has 200 photos of the skin, including 40 cases of melanomas and 160 of nevi, and researchers can get it for free by filling out an online form (PH2-A, 2021). In the MED-NODE Dataset, 70 melanoma patients and 100 cases of nevi are documented in the 170 clinical pictures and the dataset can be downloaded for free (Giotis *et al*., 2015). Across 12 categories, the Asan Dataset contains 17,125 photos of clinically diagnosed Asian skin conditions. It's free to use for academic study (Han *et al*., 2018). The Hallym Dataset contains 125 clinical images and SD-198 contains 6584 clinical photos of 198 skin disorders. Class sizes are maintained in the SD-260 dataset. However, the SD-198 dataset only has 10–60 pictures for each category. The 20,600 pictures illustrate 260 different skin conditions (Yang *et al*., 2018). DermNet NZ has a large and diversified collection of clinical, dermoscopic, and histological photographs. The images can be purchased in high-resolution versions (DermNet, 2021). Among the 1011 images in Derm7pt are 252 images of melanoma and 759 images of nevi (Kawahara *et al*., 2018). The Cancer Genome Atlas has 2871 pathological skin lesion slides. It is open to the research community (Goyal *et al*., 2020). PAD-UFES-20 (31), PAD-UFES-20 (31), PAD-UFES-20 (31), PAD-UFES-20 (31), dataset comprising 2,298 clinical photos collected with smartphones, 21 patient features, and six different skin lesions. Images from dermoscopy and clinical settings differ significantly from those from other sources and the amount of patient-specific attributes also varies widely. In contrast to

clinical photographs, dermoscopy images reveal more of the skin's surface and are unaffected by light or camera resolution.

Difficulties of S.C.D.

Identifying skin lesions is difficult because of various image types and sources, as depicted in Fig. 2. The look of human skin color varies greatly, making skin identification challenging and time-consuming. The following are some of the issues posed by the complex visual qualities of skin lesions images (Naji *et al*., 2019):

(i) The wide range of skin lesions adds to the intricacy of these images and makes precise skin lesion diagnosis extremely challenging. Lesion location, size, and shape are all extremely variable. Thus, most image analysis approaches require image preprocessing to analyze skin lesion images accurately
(ii) During the acquisition of an image, noise is introduced. In the presence of noise and artifacts, skin lesion photos may be difficult to identify. Human and even computer-assisted approaches to skin lesion segmentation can influence an image's interpretation if these compromising signals are present in the picture. Hair, bubbles, and blood vessels are just a few examples
(iii) The presence of fuzzy and uneven boundaries in some skin lesion images complicates several contour refinement and boundary localization procedures. Preprocessing skin lesion images for simple asymmetry prediction can be difficult
(iv) Low contrast from adjacent tissues can also be observed, adding to the problem. The low difference between the lesion and the surrounding skin makes segmentation challenging
(v) The lesion's color texture, light beams, and reflections influence an image's lighting

Deep Learning Strategies

A deep learning system can be used in a medical setting to take a picture of a skin lesion and figure out if the lesion is likely to turn out to be skin cancer (Fig. 3). To learn visual features from the data, neural networks can be trained with tagged photo data using convolutions and subsampling. Weights in later layers of a neural network are adjusted to maximize the link between image features and categorization of the input images, much like it does while learning superficial image characteristics. Figure 3 illustrates the DL strategy's classification process and Fig. 4 shows how deep learning models classify photos. The initial step is to choose a model architecture. Deep CNNs are frequently used in image classification applications (Reis *et al*., 2022). The model already includes the entire lines and forms required for image recognition.

Weights in a neural network are used to distinguish predictions from actual labels. When the model can identify the most critical features of an image, it can minimize the loss. A second validation set is employed during training to better understand the model's performance and reduce overfitting. A model's performance is tested on a different test set once trained. Data from another hospital system could be used to test the generalizability of a clinical deep learning algorithm. These models could be prospectively tested in a clinical context in the future. Deep learning systems use clinical, radiological, and pathological imaging data to predict cancer diagnosis. Four questions aid in developing and applying clinical deep learning algorithms (Fig. 5). With this in mind, we investigate the future use of deep learning in cancer diagnostics. Healthcare uses deep learning to automate tasks that people now carry out at a more incredible speed and accuracy. An algorithm must be compared to human judgments or another set of 'ground truth' diagnoses or classifications to establish how effectively it works. There are many clinical uses of deep learning and the model is built utilizing these labels to train it. If the classification task is typical of real-world clinical workflows, deep learning articles should be evaluated to see if the comparison is correct.

When evaluating a model's performance, examining the data supporting it is crucial. Patient inclusion and exclusion criteria are used in the data adjudication process. You must have adequately labeled training/validation/test datasets to train and test deep learning algorithms. Data adjudication is essential since "garbage in" can lead to "garbage out" for algorithms. To achieve this goal, data labeling should have a gold standard for each machine learning process. Pathological confirmation is the gold standard in skin cancer clinical care. A model's generalizability can be determined by evaluating how it is considered. Overfitting occurs when a model performs well on training data but fails on testing data. Sensitivity, specificity, and positive predictive value evaluate machine learning algorithms. A random classifier represents a diagonal line with a slope of 1 and an intercept of 0. The Receiver Operating Characteristics curve (R.O.C.) on the x-axis depicts the relationship between sensitivity and 1-specificity and the association between sensitivity and 1-specificity on the y-axis. The R.O.C. curve's A.U.C. determines that the classifier can distinguish between different classes.

The model's performance on an independent test set should be the basis for the evaluation measures (Liu *et al*., 2019). Despite the differences between real-world and retrospective data, future applications and evaluations must thoroughly demonstrate the generalizability of a deep learning system for therapeutic activities.

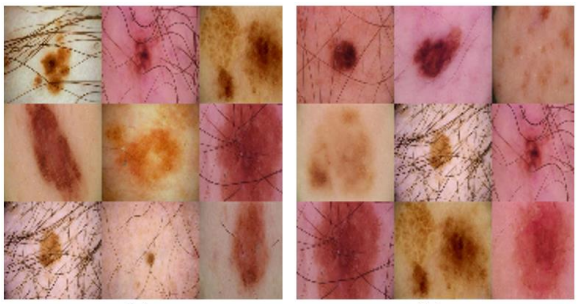

Fig. 2: Images from a melanoma cancer dataset (a). malignant (b) benign

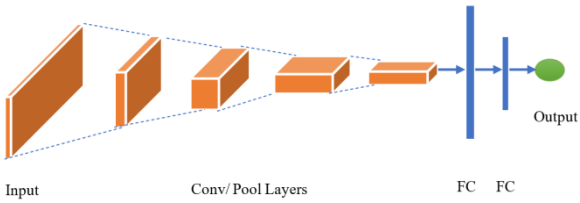

Fig. 3: Classification process using CNN

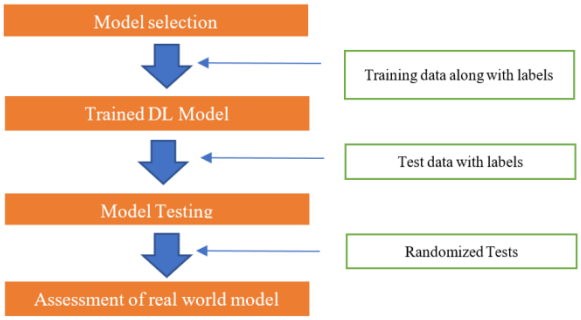

Fig. 4: The classification process of deep learning

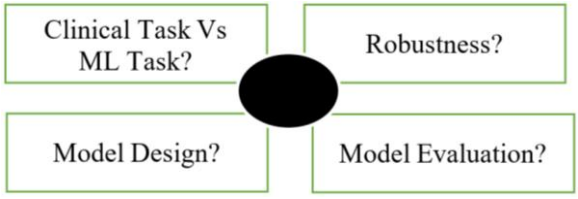

Fig. 5: Four factors to help evaluate medical deep learning algorithms

Recommendation

In the hands of a physician, an A.I. tool that has been appropriately evaluated may enhance processes, improve accuracy and save costs. Numerous aspects should be considered while developing A.I. algorithms for cancer diagnostics. Even if the A.I. algorithms discussed above don't reflect the clinical function, it is still viable to interact with healthcare experts. Primarily care physicians and nurse practitioners typically provide a comprehensive skin assessment on patients before referring them to dermatologists.

Algorithms developed by Esteva *et al*. (2017) and Liu *et al*. (2020) can accurately identify benign, malignant, and non-neoplastic lesions as a triage aid for non-specialists making dermatology referral decisions. A.I. can be used to create tools that help doctors enhance their practices, but it can also be employed to carry out previously impossible jobs. A.I. systems can recognize patterns humans cannot see, opening up many new creative possibilities. Without particular stains or testing, a human pathologist, for example, cannot detect whether genetic changes are present in histopathology (Coudray *et al*., 2018). Determining the origin of an enormous tumor, especially when the disease is metastatic and poorly differentiated, is another hurdle in cancer diagnosis and treatment. According to human assessments of the condition, about 3% of cases of metastatic cancer have no apparent cause.

The scientists (Jiao *et al*., 2020) used somatic passenger mutations from whole-genome sequencing of 24 tumor types to construct a deep learning method for detecting the primary tumor. Their algorithm exhibited 88 and 83% accuracy on separate primary and metastatic tumor samples. These preliminary findings demonstrate how molecular data and machine learning might be coupled to discover new cancer knowledge. The use of artificial intelligence in cancer diagnostics has the potential to transform a wide range of fields. Physicians can play an essential role in the design and development of machine learning. They pay close attention to how the algorithm tries to clinical practice, its development, and its evaluation.

Materials and Methods

Deep neural networks are essential in skin cancer detection and the networks are made up of many nodes. After being programmed, neural networks take on the role of subject matter experts in their chosen fields of application. Images were categorized and our study identified skin cancers using neural networks. There are a variety of approaches to training a system to detect skin malignancies and this study mentions five of them.

An ANN-based strategy falls under the first of these categories. ANN is a nonlinear statistical method for predicting the outcomes of data. Three layers of neurons make up an ANN based on the human brain's structure. Neurons in the second/intermediate layer receive information from their counterparts in the input layer. The strata that are buried are intermediate ones. Hidden layers are common in ANNs. Intermediate neurons feed Third-layer output neurons. Many complex correlations between input and output layers are learned using backpropagation. Figure 6 depicts the fundamental

interconnections between nodes at various layers (The 'P' in the diagram denotes a layer). Malignant and benign skin lesions can be distinguished using a method developed by Xie *et al*. (2016). There were three stages to the recommended system. First, lesions were removed from images using a self-generating neural network. Step two involved extracting tumor borders, texture, and color data. The system detected 57 features, including seven new ones linked to the margins of lesions. Using P.C.A., the dimensionality of the traits might be reduced to a minimum, allowing the best set to be selected. Finally, an ensemble model was used to classify the lesions, increasing classification performance. SVM, K.N.N., random forest, AdaBoost, and other classification systems compared the suggested system's results. The proposed model surpassed the different classifiers with 91% in terms of sensitivity.

After examining three different ANN learning algorithms, Masood *et al*. (2014) developed an automated skin cancer diagnostic method based on artificial neural networks. With more epochs, the sensitivity of S.C.G. grew to 92.6%, but the specificity (95.1%) and efficiency of the L.M. algorithm in diagnosing benign lesions remained unchanged. Early melanoma skin cancer detection using classification (Cueva *et al*., 2017) To extract features from lesions, the ABCD rule was used. Asymmetry in the form, borders, color, and mole diameter is ABCD. Mumford–Shah and Harris Stephen algorithms extracted mole asymmetry and boundaries. The melanoma detection threshold was set at 6 mm in diameter for melanoma moles. The suggested method divides moles into three categories: Standard, rare, and melanoma, using a backpropagation feedforward ANN (Jaleel *et al*., 2012).

The second category includes *CNN-based strategies*. The investigators used a CNN with five levels to divide skin lesions into three categories, one of which was melanoma, a potentially fatal form of skin cancer, (Kawahara *et al*., 2016). The suggested CNN classifier attained 95% accuracy after training and testing on dermoscopic images from the PH2 dataset. Additionally, when the number of layers in CNN was extended to 14 layers on dermoscopic pictures from the ISIC dataset, a higher accuracy rate of 97.78% was found (Ho *et al*., 2021). Regardless, adding layers consumes more resources and increases the complexity of processing. Rashes and skin cancer detection have both been classified using CNN. Deep Learning Studio was used by Sagar and Jacob (2021) to create Deep Learning using a Model-Driven Architecture. The researchers introduced the studio suite features to make developing a Deep Learning Model easier. The researchers explained how to prepare dermal cell images and showed how the D.L.S. model might be used to locate cancer cells. Based on medical photos, the model had an A.U.C. of 99.77% for detecting cancer cells.

The classification phase's training model (Jojoa Acosta *et al*., 2021) used a Deep Residual Network (DRN). A decent accuracy was achieved when the Fully Convolutional Network (FCRN) was used for classification. However, because the app is designed to classify medical images, the incidence of false positives must be decreased to be helpful in medical settings. To achieve this, the importance of memory must be greater than the importance of overall study accuracy. The third category includes hybrid strategies. Several researchers have described approaches for categorizing skin lesions using well-known deep learning models or recognizable features. Despite this progress, there is a scarcity of research on merging current characteristics with deep learning models. Developing a reliable method for extracting local and global traits would significantly improve skin distinction. Motivated by these considerations, researchers (Burguillo and Dorronsoro, 2013) built an integrated model that extracts global-local characteristics by combining LBP and deep Conv features. Several studies have combined Local-DNN and Global-DNN to achieve superior results. Researchers commonly use segmentation algorithms to eliminate background noise from visual imagery. Lenhardt *et al*. (2013) used a hybrid technique that included three models to predict lesions. Two typical machine learning classification models were trained using a collection of characteristics that specify skin lesions' color, texture, and boundaries. By majority voting, the models were then hybridized to improve performance.

Data augmentation and transfer learning fall into the fourth category. Learning new skills by applying what you've already learned to previously taught ones is called "transfer learning." Adaptation of domain and transfer learning improves generalization capability in a subsequent context using a single training set (Lu *et al*., 2019). A large dataset is required to train a new DCNN model, which is a disadvantage for the model because existing skin lesion datasets lack annotated images in large datasets. Theoretical knowledge of transfer learning is critical to overcoming the barrier. The essential distinctions between regular machine learning and transfer learning are depicted in Fig. 7. Transfer learning can deal with small datasets, improving model learning performance (Zhai *et al*., 2019). The ability to adapt to obstacles can be obtained by fine-tuning trained models (Mahbod *et al*., 2019). In addition, approaches for supplementing small datasets have been widely used in categorizing raw images and melanoma. The problem of data scarcity, which leads to overfitting in melanoma classification, is addressed by augmenting limited datasets. The notion that data annotation does not change the semantic value of labels is central to picture augmentation.

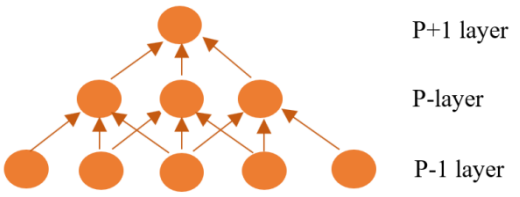

Fig. 6: Layers in neural networks

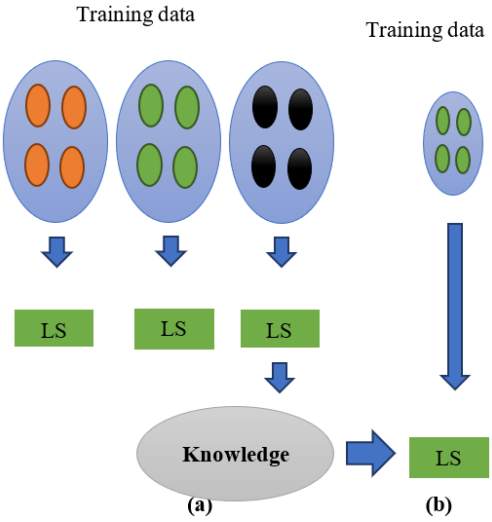

Fig. 7: The approach of (a). Machine learning (b). Transfer learning

Researchers (Ashraf *et al*., 2020) advocated using R.O.I.s to automate the extraction of discriminative features. Through data supplementation, the system can also rectify a class imbalance. Improvement of low-level feature learning of the AlexNet model has been achieved with an efficient false positives reduction in the CAD system thanks to the suggested system's transfer learning. The Error-Correcting Output Codes (ECOC) approach can be used to transform multiple-class classification problems into a two-class classification type. DenseNet, Efficient Net, MobileNet, and Inception V3 were the CNN variations studied (Gavrilov *et al*., 2019).

According to the statistics, CNN Xception had a higher accuracy rate of 89%. In Harangi *et al*. (2020), a DCNN design for binary classification with several classes delivers improved result reliability with little probability. A similar CNN architecture (GoogLeNet Inception-v3) was used to learn the simultaneous categorization of multiple and binary classes. According to Demir *et al*. (2019), the Inception-v3 architecture outperformed the ResNet-101 architecture. Salian *et al*. (2020) Use ImageNet's pre-trained data to train the DenseNet121, ResNet50, and VGG11 models. The modelsincreased the dataset size, resulting in increased model efficiency. A 90% accuracy rate was achieved throughout training with a low loss rate. The PH2 and HAM10000 datasets were used in pre-trained novel models (VGG16 and Mobilenet), subjected to two conditions (i.e., without augmentation and augmentation). The performance of the two new models was then compared to custom-made deep learning architecture. A well-thought-out model from the ground up would perform just as well. Mobilenet and the tailored model performed well in terms of inaccuracy rate performance. The results showed that data augmentation did not influence classification compared to non-augmented data.

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In the past, intricate and sophisticated models increased detection accuracy. There is a shortage of research into the differences and similarities amongst different classes of lesions. Using a sophisticated model with a high computing cost could be troublesome in the real world. Researchers in

Wei *et al*. (2020) used a simpler model to differentiate between different lesion recognition models. A pre-trained lightweight network incorporates dermoscopy image classification and lesion feature discriminant branches into the model. The model performs shared training for each branch network, allowing lesion type while establishing lesion feature similarity. As a result, it is possible to extract additional discriminative lesion features. Researchers are using Ensemble-based techniques to increase the accuracy rate performance of individual approaches.

The fifth category includes Generative Adversarial Network (GAN) based methods created by Goodfellow *et al*. (2020). The GAN model is a generative model that uses adversarial deep neural networks to train. The GAN learns generative models for data distribution using an adversarial technique. The GAN has long been regarded as the most prominent generative model in A.I. research. On the other hand, deep architecture necessitates using actual samples to learn meaningful representations. For supervised learning, large datasets for medical imaging are currently unavailable. This is partly due to the time-consuming and costly process of classifying and obtaining datasets, requiring sophisticated technology and expert human judgment. Researchers have been unable to use deep learning in medical imaging entirely due to a lack of large-scale datasets (Rashid *et al*., 2019) that created pictures resembling dermoscopic images using GANs. The photos are combined with augmented trained data to improve deep CNN's skin lesion categorization. The discriminator and generator, as mentioned in algorithm one, can be obtained by using formal expressions as follows:

$$\nabla\theta_d = \frac{1}{m}\sum_{n=1}^{m}\left[\log D\left(x^i\right) + \log\left(D\left(G\left(z^i\right)\right)\right)\right] \quad (1)$$

$$\nabla\theta_g = \frac{1}{m}\sum_{n=1}^{m}\left[-\log\left(D\left(G\left(z^i\right)\right)\right)\right] \quad (2)$$

The letter 'z' represents noise with a uniform or normal distribution, ' G' represents the picture generator, and 'm' is the number of noise and samples produced due to data production. 'D(x)' computes the likelihood that 'x' is derived from data rather than the generator distribution.

Furthermore, stochastic gradient descent trains GANs that adhere to the *d* and *g* parameters. Sedigh *et al*. (2019) proposed a CNN algorithm, a GAN variation, to generate mimic images of skin cancer to compensate for the shortage of training data. Figure 8 depicts the structure of the GAN algorithm. Work in Qin *et al*. (2020) introduced GAN to produce style-based false skin lesion images, closely connecting to the earliest known GAN algorithm. The proposed work alters the generator's style control structure and noise input. It modifies the generator and discriminator to produce high-quality imitation skin lesions quickly. For the first time, an image classification system was developed using a neural network that had already been trained. The training set will be supplemented with mock skin lesion photographs, resulting in increased classification performance.

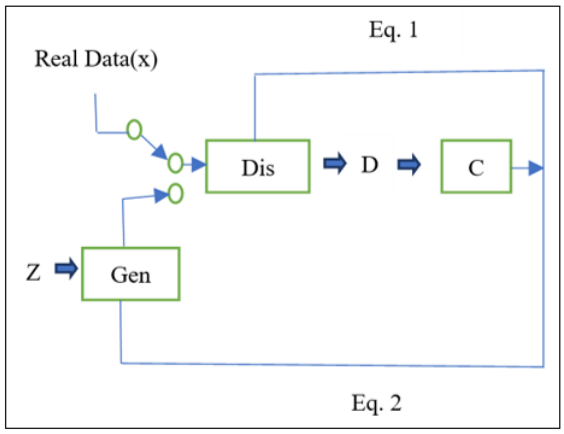

Fig. 8: Structure of GAN algorithm (Des = Discriminator, Gen = Generator)

Evaluation Metrics

Using DCNN architectures to predict skin lesions can improve accuracy, sensitivity, and specificity. True Positives (T.P.) are positive cases that are accurately predicted, while False Negatives (F.N.) are negative instances that are wrongly predicted, according to Eq. (3) to Eq. (6). True Negatives (T.N.) are bad events that have been correctly foreseen. Finally, False Positives (F.P.) are instances where a positive outcome is predicted mistakenly. Correctly identified skin lesions are referred to as recall or sensitivity. In the medical field, classification applications necessitate a high level of sensitivity because it indicates the system's worthiness:

$$T.P.R = \frac{TP}{(TP + FN)} \quad (3)$$

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (4)$$

$$TNR = \frac{TN}{(TN + FP)} \quad (5)$$

$$PPV = \frac{TP}{(TP + FP)} \quad (6)$$

Discussion

DL algorithms for skin cancer detection have gained popularity recently due to their accuracy. Recent research focuses on deep convolutional neural networks. The goal is to improve skin lesion detection in CAD systems when considering transfer learning (pertained network), fine-tuning, ensemble approach, data creation, and augmentation. Skin cancer categorization and detection research are summarized in Table 1, including recent studies' results.

Table 1: Recent research works on S.C.D. using ML and DL approaches

Ref.	Architecture	Description	Dataset	Evaluation metrics
Saad Ali *et al*. (2019)	PGAN	A stabilizing strategy was used to improve a generative model.	ISIC 2018	Accuracy = 70%
Jojoa Acosta *et al*. (2021)	ResNet 152	based on masks et CNN extracted the region of interest and ResNet152 classified the data	ISIC	Accuracy = 91%, Sensitivity = 83% Specificity = 93%
Sagar and Jacob (2021)	ResNet 50 (Transfer learning)	The proposed model outperformed other transfer learning architectures	ISIC	Precision = 95% F1-score = 86% Accuracy = 94% Recall = 78%
Subha *et al*. (2020)	CNN	Using CNN, the authors detected and identified skin cancer from rashes photos	A/N	Accuracy = 81%
Alkarakatly *et al*. (2020)	5-layer CNN	Diagnosing three types of skin lesions (melanoma, a malignant skin cancer lesion)	PH²	Accuracy = 95%
Kadampur and Al Riyaee's (2020)	D.L.S.	Created dermal cell categorization and skin cancer diagnosis models without Deep Learning Studio experience	HAM10000	AUC = 99%
Vinay *et al*. (2020)	DRN	In a two-stage network, melanoma and non-melanoma images are diagnosed	ISIC	Accuracy = 88%.
Xiao and Wu (2020)	Resnet-50, DenseNet-121	The Global–Local model now includes customizable and deep Conv elements to better portray skin cancer	ISIC-2017	84% on MM and 91% on SK
Daghrir *et al*. (2020)	CNN, K.N.N., and SVM	Hybrid methods that take advantage of one method's advantages to detect melanoma in the skin	ISIC	Accuracy = 89%
Mohamed *et al*. (2019)	AlexNet	The AlexNet model's initial low-level feature layers were transferred and reviewed for augmentation to acquire the best results	Derm-IS	Accuracy = 98%
Rashid *et al*. (2019)	DC-MobileNetV1 DC-DenseNet121	The model for detecting skin cancer is simple and uses a fine-grained classification code to help it make distinctions	ISBI 2016	Accuracy = 96%
Bisla *et al*. (2019)	ResNet50 GANs	Using a GAN-based data augmentation technique, we can precisely diagnose skin lesions	ISIC 2018	Accuracy = 96%
Nida *et al*. (2019)	14-layer CNN	Deep convolutional neural networks are used to create an autonomous dermoscopic detecting pattern.	ISIC ISIC 2017,	Accuracy = 98% AUC = 92%
Rashid *et al*. (2019)	DCGAN	DCGAN used to augment the dataset	2018 and, PH2	Accuracy = 87%
Bisla *et al*. (2019)	GAN	Classification is done based on generator and discriminator	ISIC 2018	Accuracy = 96%
<<continuation of Table>>				
Nida *et al*. (2019)	Deep region CNN + Fuzz c-means	As a result of this combination, illness detection was more accurate	ISIC	Accuracy = 93% Sensitivity = 96% Specificity = 94% F1-score = 94%
Albahar (2019)	2-layer CNN with custom regularized	A proposed regularization technique for controlling complexity penalized a classifier's weight matrix's dispersion value.	ISIC	Specificity = 93% AUC = 97% Sensitivity = 94% Accuracy =97%
Rahi *et al*. (2019)	Transfer learning	They are using pre-trained data-based architectures. VGG11, RESNET50 and DENSENET121 are among the transfer learning models employed	HAM10000	Accuracy = 90%
Gavrilov *et al*. (2019)	Xception	Pathology and normal classification of skin lesions	ISIC	Accuracy = 89%
Li *et al*. (2019)	Ensemble Network	Clinical criteria may not have called for discovering novel biomarkers for diagnosing lesions, but dermatologists are well-suited to undertake such a project	ISIC-2018	Accuracy = 85%
Pacheco *et al*. (2019)	CNN+SE-Net	A classifier ensemble to diagnose eight different skin lesions	ISIC 2019	Accuracy = 91%
Rashid *et al*. (2019)	GANs	GANs can be used to improve the DCNN categorization of skin lesions by augmenting the existing training set	ISIC 2018	Accuracy = 86%
Sedigh *et al*. (2019)	S-CNN	They generate mock medical images of skin cancer based on the primary dataset to detect skin cancer	ISIC	Accuracy = 53% Accuracy = 71% (with GAN)
Dorj *et al*. (2018)	Alex Net	Identifying the four types of skin cancer	Random Internet Collection	Accuracy = 95%
Hosny *et al*. (2018)	AlexNet	Identifying three types of lesions	PH2	Accuracy = 98%
Harangi *et al*. (2020)	CNN + AlexNet + VGG	Assorting many CNNs into a centralized architecture for improved skin cancer classification efficiency	ISBI	Accuracy = 84%

Table 1: Continue

Aqib *et al*. (2017)	ANN + Fuzzy Neural Network	Lesion extraction was performed using a self-generating neural network	Caucasian, Xanthus datasets	Accuracy = 95% Sensitivity = 95%, Specificity = 94%
Mendes and da Silva (2018)	CNN + Res-Net 152	Data augmentation applied	1300 Medical images	AUC = 96% BCC = 91%
Harangi *et al*. (2018)	CNN – 1 layer	CNN + AlexNet + VGGNet, + GoogleNet	ISIC – 2017	AUC = 85% Accuracy = 84%
Mandache *et al*. (2018)	CNN	Pre-trained network with 10 layers	FF-OCT	Accuracy = 96%, Sensitivity = 96%, Specificity-97%

Open Research Issues

Recognition of skin cancer detection has dramatically benefited from advances in deep learning. The following elements may merit further consideration and attempts.

One of the most challenging aspects of employing neural networks to detect skin cancer is the substantial training required. So, the system must be thoroughly taught before adequately evaluating and interpreting dermoscopic images.

The size of the lesions varies as well. Italian and Austrian researchers collected thousands of pictures of benign and malignant melanoma lesions in the 1990s. The diagnostic accuracy of recognizing lesions ranges from 95 to 96%. It was significantly more difficult and error-prone to detect early stages and lesions as small as 1mm or 2mm.

To successfully identify skin cancer, a neural network must learn skin color. Dark-skinned people can only do this if the neural network is sufficiently trained. Skin cancer detection techniques need dark and light-skinned people's lesions.

It's also hard to identify a birthmark from malignant melanoma. In some diseases, the lesions are nearly identical. The limited variation makes image analysis and classification challenges.

The information utilized to diagnose skin cancer is heavily distorted. There are several skin malignancies, each with a different number of photos. Hundreds of photographs of common skin cancers but only a few unusual skin cancers, for example, make generalizations from dermoscopic images difficult.

The N.N. software requires robust hardware to extract the unique elements of a lesion's image. Training for deep learning-based skin cancer detection requires more computing power.

MCC, B.C.C., and S.C.C. are skin cancer more common in people over 65. Images of young people are available via dermoscopic databases. There must be sufficient pictures of persons above 50 for neural networks to detect skin cancer in older adults.

Automated skin cancer detection relies on preprocessing and detection of lesion borders. Automated skin cancer diagnosis systems could benefit from optimization methodologies like artificial bee colonies and particle swarm optimization.

The risk of developing melanoma runs in families at less than 1%. In addition to environmental concerns such as increased U.V. exposure, skin cancer risk variables are being used to improve existing deep learning algorithms.

Conclusion

Cancer of the skin continues to be the leading cause of death among people all over the world. A diagnosis must be made as soon as possible because the condition is fatal. In the fight against skin cancer, there has traditionally been a deficit of knowledge and cutting-edge technology. In this study, an investigation into the current state of DL architectures for the detection and classification of skin cancer was carried out. When data are not labeled, the risk of overfitting increases. Transfer learning, fine-tuning, the ensemble approach, data creation, and augmentation are all examples of potential alternatives. Image segmentation accuracy was evaluated using several metrics, including sensitivity, specificity, accuracy, the F-score, and the Jaccard index. The performance of many methods was superior to that of others that did not meet the required criteria, such as accuracy of segmentation of greater than 90%. According to the study's findings, better segmentation and analysis of lesions can be achieved through dermatoscopic images containing fewer artifacts and more detailed characteristics. However, eliminating or significantly reducing the number of artifacts is often necessary to segment data successfully. In the future, image segmentation of skin lesions will improve edge detection accuracy while simultaneously addressing issues such as automation, compute performance, image noise, and enhancement. For applications such as medical imaging, where large-scale training datasets are technically unattainable, creating a comprehensive dataset containing skin lesion samples from broad populations also includes unusual cases.

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Author's Contributions

Akepati Sankar Reddy: The article background

work, literature study, theoretical analysis and comparison, draft preparation and editing and visualization of the diagrams.

Gopinath M. P: The supervision, review of the work, correspondence and administration.

Ethics

This article was written by the author and does not contain any previously published content. It has been confirmed by the author who serves as the corresponding author that all of the other writers have seen and given their approval to the article, and that there are no ethical concerns involved.

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