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CLASSIFICATION OF SKIN CANCER BASED ON DEEP LEARNING USING CONVOLUTIONAL NEURAL NETWORKS – OPPORTUNITIES AND VULNERABILITIES A SYSTEMATIC REVIEW

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ABSTRACT

Convolutional Neural Networks (CNNs) have outperformed dermatologists in the classification of skin lesions related to skin cancer, potentially saving lives through earlier diagnosis. By just installing an app on their mobile devices, people will be able to self-diagnose their cancer. By the end of 2021[28], 6.3 billion people are expected to have used the subscriptions to diagnose themselves with skin cancer. This study shows its findings after reviewing a large number of research articles on CNN-based skin lesion classification. Thanks to recent advances in machine learning algorithms, the rate at which skin lesions are erroneously identified has decreased as compared to dermatologist categorisation. This study looks at the approaches that have been taken, the effectiveness of those approaches, and the development of CNN in the successful classification of skin cancer subtypes. While deep learning with CNN gives advantages over a dermatologist, it also has certain disadvantages when misclassifying photos depending on symptoms and criteria. We also address these weaknesses in this overview research. We searched the Science Direct, PubMed, Elsevier, Web of Science, and Google Scholar databases for published original research publications. From the web publications we looked for, we selected articles with sufficient data and information about the authors' study and created an overview of the authors' approaches and methodologies. There is currently a lack of review literature addressing the merits and drawbacks of applying deep learning to the classification of skin cancer. Advances in deep learning and machine learning technology can eliminate human error and prevent errors and classifications. Along with their limitations, we will also discuss the benefits of using CNNs for deep learning.

1.0 Introduction

One of the deadliest forms of cancer is skin cancer, which is brought on by abnormal cell proliferation. Three major types of skin cells are melanocytes, basal cells, and squamous cell carcinomas. Of the two types, melanocytes are the more dangerous. It is separated into two categories: those with melanocytic paperwork and those without. Because benign and malignant melanoma can be hard to distinguish from one another, dermatologists frequently classify melanoma incorrectly. Melanoma, the 19th most frequent malignancy, has seen a 53% annual increase in occurrences, partly due to UV exposure [1,2]. It is more dangerous than squamous cell carcinoma and basal cell carcinoma, because it spreads throughout the body more quickly. Early detection and appropriate classification of the right form of cancer is critical to reduce mortality.

The dermatologist's initial diagnostic procedure for a malignant lesion involves a visual inspection of the afflicted region. This often leads to false positive results, especially when the cancer is still in its early stages. Lesions of a certain kind can be similar to one another. Therefore, if necessary, adjust the diagnosis to avoid complications. The accuracy percentage of a dermatologist in doing a basic visual examination used to range from 65 to 80 percent [3]. Dermatologists seldom reach sensitivity levels beyond 80% [15]. A unique high-resolution and magnifying camera lens was used to take dermoscopic images of suspected lesions in addition to a visual assessment. During this recording procedure, the effect of light on the image is regulated by using filters to highlight deeper layers of skin and eliminate reflections in the skin.

The accuracy price rose by using an extra 49% with this additional technical guide [4]. A dermatologist's visual exam followed by using dermoscopic photographs has an typical accuracy price of seventy five–eighty four percentage [5, 6]. pc imaginative and prescient may be useful inside the analysis of skin cancer due to the problems concerned in the usage of the human eye for analysis. pores and skin cancer may be identified and classified using both deep mastering or traditional gadget getting to know. In order for the learning set of rules to lessen complexity in conventional system learning techniques, a site professional must pick out the implemented capabilities and lead them to extra seen. within the field of machine mastering, the deep mastering algorithm utilizes artificial neural networks, which are algorithms that draw proposal from the shape and operations of the human brain. An artificial Neural community (ANN) can be educated with a massive quantity of images depicting benign and malignant conditions.

The image's maliciousness or benignity may be decided by means of the model itself thru the learning of nonlinear interactions. therefore, characteristic extraction in deep studying does not require area information. on this work, we use CNNs (Convolutional Neural Networks), a form of ANN, to observe deep learning.

2.0 Convolutional Neural Networks

Convolutional neural networks are the type of deep neural networks that are most frequently used in image processing. It's utilized for organization composition, picture classification, and image recognition. CNN is a great way to gather and analyze local and global information because it combines unique characteristics like curves and edges to build extra sophisticated capabilities like forms and corners [7]. Convolutional, nonlinear pooling, and totally linked layers are some of CNN's hidden layers [8]. In a CNN, multiple completely linked layers are used to monitor multiple convolutional layers. The three main types of layers used in CNN are convolutional layers: pooling layers, absolutely related layers, and absolutely linked layers [9]. Scientific photo recognition, segmentation, and type have advanced significantly thanks to computerized CNN-based device learning frameworks [10]. A fully convolutional residual community (FCRN) with 16 residual blocks was hired to increase efficiency during the segmentation process. The advocated technique makes use of a mean of SVM and different classifiers for type. In melanoma classification, it confirmed an accuracy of 85.5 percent with segmentation and 82.eight percentage without segmentation [11]. This recommended a multiscale CNN. The Inception v3 framework was quality-tuned at two density scales of the input lesion pics: coarse scale and finer scale. To capture the shape capabilities of lesions as well as normal contextual statistics, the coarse scale changed into used. The finer scale, alternatively, collected textual information approximately the lesion to distinguish between numerous sorts of skin lesions.

There are methods to use CNNs to categorize pores and skin lesions. A CNN that has been pre-skilled on big datasets like ImageNet may be used as a characteristic extractor [12]. In this example, the type is finished by means of some other classifier which can aid vector machines, artificial neural networks, or ok-nearest associates, amongst other strategies. 2d, a CNN may right now research the association between the raw pixel data and class labels way to stop-to-cease learning. unlike the machine learning approach, characteristic extraction does now not require human revel in. It is far now not idea of as a standalone phase because it is now an vital a part of the categorization stage. The two types of processes that the CNN trains through are learning from scratch and transfer learning. End-to-end learning separates the processes into these two categories.

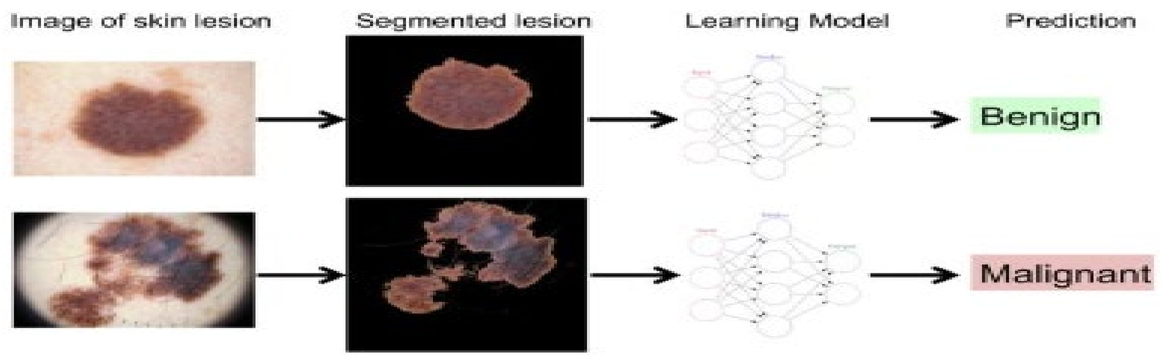

Figure 1. Learning model

3.0 Methods

A complete seek was executed on Google student, Elsevier, PubMed, and ResearchGate to find important research articles on the usage of deep studying and convolutional neural networks for pores and skin type. examining the performance metrics in element confirmed that deep getting to know can also notably beautify the type of skin most cancers, outperforming a dermatologist in terms of accuracy.

Evaluation metrics

A classifier assigns each object to a class. because this mapping is frequently no longer best, gadgets can be mapped to the incorrect elegance. to assess a classifier, one desires understand the authentic magnificence of the items. to assess the high-quality of the category, the elegance that the classifier assigned is contrasted with the real magnificence. consequently, the following four agencies may be fashioned from the objects: [13].

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.

Accuracy

Based on the cardinality of these subgroups, statistical quantities for the classifier can now be calculated. Although accuracy is a commonly used quantity, it is merely a useful measure.

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

if the different classes in the data set are approximately equally distributed. Accuracy is calculated as follows:
It indicates the percentage of objects that were classified correctly.

Sensitivity

two in addition critical metrics that can be carried out even if the distribution of the exclusive classes isn't uniform are sensitivity and specificity. The ratio of efficaciously labeled high quality items to all advantageous objects in the statistics set is displayed as the sensitivity, that is calculated as follows.

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

Specificity

Specificity, which may be computed as follows, represents the ratio of efficiently categorized bad items to all bad items within the to be had statistics set.

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

The output of a binary classifier is known as a chance distribution during training. Items having an output price greater than zero are classified as binary. Fives are typically allocated to positive elegance and devices with less than zero cost of production.5 are attributed to the lackluster elegance. There is a trade approach that is entirely dependent on the receiver running function (ROC). The threshold used for type varies systematically between zero and 1, and the sensitivity and specificity are decided for every selected threshold. The ROC curve is calculated with the aid of plotting sensitivity in opposition to 1-specificity and may be used to evaluate the classifier. The similarly the ROC curve deviates from the diagonal, the better the classifier. A suitable standard degree of the curve is the vicinity underneath the curve (AUC).

4.0 Skin Lesions Classification Based on Convolution Neural Networks: Opportunities

4.1 Skin Lesion Classification Using Convolutional Neural Network as a Feature Extractor

[14]. They segmented the data using CNN's U-Net algorithm. To extract the features from the segmented images, they employed the Edge Histogram (EH), Local Binary Pattern (LBP), Gabor method, and Histogram of Oriented Gradients (HOG). To determine whether the condition is benign or melanoma, features taken from the aforementioned techniques were fed into the Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes (NB), and Random Forest (RF) classifiers. 900 dermoscopic images are used in this experiment. For images, the International Skin Imaging Collaboration (ISIC) is utilized. Ninety percent of the 900 segmented images are used as training data for classification, while the remaining ten percent are used as test data.

The classifiers were fed these features. With the SVM classifier, an accuracy of 85.19 percent was attained. The extracted features' classification methods' experimental results. SVM predicts 50 percent for recall, 85 point 19 percent for precision, and 46 percent for F1_score. Naive Bays classification predicts 45 point 62 percent for precision.

[15] Ten distinct forms of cutaneous lesions were classified the use of a linear classifier. The final layer of AlexNet become replaced with a convolutional layer. additionally, an AlexNet became hired to extract features. [16] the slightly changed AlexNet above changed into tested the usage of 1300 clinical pictures from the public Dermo-match image database. most of the 1300 scientific pix inside the collection, 11 wonderful sorts of pores and skin lesions have been determined. a total of 81.8% accuracy became acquired for the dataset that comprised ten different types of pores and skin lesions.

[16] used the vector-based SURF method to find lesions' patterns. The features that were found are classified using a multi-SVM classifier in order to determine the type of lesion. The outcomes using this system were 96.42 percent specificity, 86.53 percent sensitivity, and 86.37 percent accuracy. 4 distinct types of skin lesions totaling 611 data photos were used.

4.2 Skin Lesion Classification Using Convolutional Neural Network as End-to-End Learning

4.2.1 Transfer Learning Using a CNN

[13] completed the ISIC 2018 task successfully. They made use of the HAM10000 dataset [14]. 10015 pictures were utilized in training and validation. Eighty percent were utilized for training and twenty percent were used for validation. 6705 of the total photos were of melanocytic nevi, while 115 of the images were classified as minor dermatofibromas. Some of the remaining photographs are of melanomas; the others are of various types. They trained a number of CNN models, such as DenseNet 201, ResNet152, and Inception V4. They pre-trained their models using the ImageNet dataset. They obtained a confusion matrix of 0.96, 0.96, and 0.96 65 for melanocytic nevus, respectively, using DenseNet201, ResNet152, and Inception V4.

They used DenseNet201, ResNet152, and Inception V4 to obtain a confusion matrix for dermatofibromas of 0.86, 0.94, and 0.82 65, respectively. They used DenseNet201, ResNet152, and Inception V4 to achieve a confusion matrix of 0.65 for melanomas, and 0.73, 0.76, and 0.65, respectively. They were able to obtain a 2 percent improvement in the confusion matrix, which is 0.98 for melanocytic nevus, by cropping images for training and validation using DenseNet201. In [17], CNNs trained on ImageNet datasets and a network trained on the Dermnet-A skin disease atlas were employed. They achieved an accuracy of 89.3 percent, a sensitivity of 77.01 percent, and a specificity of 93.1 percent using a popular CNN known as AlexNet for classification. used a CNN that was trained on 129,450 photos, 3374 of which were captured using a dermoscopic tool and represented 2032 different types of skin lesions.

[18]. This study contrasted benign nevi and malignant melanomas with keratinocyte malignancies. Seborrheic keratosis on both sides was controlled. The GoogleNet Inception v3 model was used for categorization.

Following testing using test data, the CNN achieved ROC-AUC of 0.94 and AUC-ROC of 0.96 for carcinomas and 0.96 for melanomas when classifying melanomas using dermoscopic pictures.

[21] They put forth a brand-new prediction model that uses a cutting-edge regularization method to categorize a lesion as benign or malignant. It is a binary classifier, then. The ISIC dataset comprises 2400 images for validation and 5600 images for CNN training. The accuracy of this suggested model in differentiating between benign and malignant tissue was 97.49

percent. CNN's AUC-ROC performance is computed for various scenarios using an integrated novel regularization. The seborrheic keratosis vs. lesions of basal cell carcinoma is 0.93. Nevus versus melanoma lesion has an AUC of 0 point 77.

For solar lentigo versus melanoma lesion and seborrheic keratosis versus melanoma lesion, respectively, the AUCs obtained are 0.86 and 0.85.

[23] They used various approaches to apply transfer learning to the AlexNet model. In this study a SoftMax layer was used in place of the classification layer in one method; the architecture's weights were adjusted in another; and the dataset was expanded using a fixed and random rotation angle in the third method. Segmented color image lesions can be classified as nevus, seborrheic keratosis, or melanoma by the SoftMax layer. A total of 170 images, of which 70 and 100 images for melanoma and nevus images, respectively, are used to test and verify the proposed method. The ISIC data set contains 2000 images, of which 374 are melanomas, 254 are seborrheic keratosis images, 1372 are nevus images, and 206 images of skin lesions from Derm (IS and Quest). For ISIC, 97.70 percent, Derm (IS & Quest), and 96.86 percent for MED-NODE, the accuracy was attained to a degree of 95.91 percent.

[24] This study classified eight skin diseases to examine the efficacy and performance of CNNs. State-of-the-art pre-trained architectures like Inception ResNet v2, ResNet 152, DenseNet 201, and Inception v3 are used. 10,135 dermoscopy images—10,015 from HAM10,000 and 120 from PH2—are utilized. Basal cell carcinoma, melanoma, actinic keratosis, vascular lesions, melanocytic nevi, benign keratosis, atypical nevi, and dermatofibromas are the eight forms of skin cancer included in this dataset. They performed 11% better than dermatologists, according to the findings. The optimal AUC-ROC percentages for melanoma and basal cell carcinoma are 94.40 percent (ResNet 152) and 99.30 percent (DenseNet 201), respectively, while dermatologists' values are 88.82 percent and 82.26 percent. Additionally, DenseNet201 had the highest averaged macro and micro AUC values (98.16 percent and 98.79 percent, respectively) for the entire classification.

[26] The computer algorithm the team used for this study is now openly available. They created a ResNet model and used 19,398 photos to improve it during training. They classified twelve distinct kinds of skin conditions using this newly created classifier. They obtained 0 points96 for melanoma, 0.83 for squamous cell carcinoma, 0.96 for basal cell carcinoma, and 0 points82 for intraepithelial carcinoma by classifying the Asan public dataset using the CNN.

[25] A deep CNN is skilled using 4867 clinical photograph datasets from 1842 patients at Tsukuba University sanatorium who were diagnosed with malignancies and skin most cancers among 2003 and 2016.

14 benign and malignant illnesses are depicted in those photographs. 9 dermatology trainees and thirteen board-certified dermatologists participated on this study 76.5% accuracy changed into attained for class using a skilled DCNN. With a sensitivity of 96.3% and specificity of 89.5%, DCNN turned into successful. it's miles concluded that DCNNN is a extra accurate classifier of skin lesions than dermatologists who have earned board certification.

[29] The authors used a convolutional neural network with Fisher vector encoding and an SVM classifier. They were able to tackle problems with tiny data sets by feeding the CNN with samples or parts of images rather than full images. The proposed method achieved an accuracy of 83.09 percent using 1279 skin pictures from the ISBI 2016 dataset.

4.2.2 Learning from scratch using a CNN

[27] Using dermoscopic pictures, the authors of this look at used VGGNet to categorise pores and skin lesions as cancer, nevi, or lentigines. They contrasted numerous methods of mastering, used switch studying to pre-teach CNN, and used frozen layers in conjunction with a CNN that turned into skilled from scratch. the various articles we found, this one made use of CNN classification from the beginning.

[35] Using clinical images, a two-layer CNN was trained from scratch to differentiate between benign nevi and melanoma. They used 136 photos to train the model. and 34 pictures served as the test set. The pictures are from recordings made available to the public by the University Hospital Groningen's department of dermatology. They obtained 81 percent sensitivity, 80 percent specificity, and 81 percent accuracy with this method. The results should be interpreted critically because there was a limited amount of data gathered for training and testing.

5.0 Skin Lesions Classification based on Convolution Neural Networks: Vulnerabilities

A few studies that looked at the drawbacks of classifying skin lesions with CNN were located. Our summary of this research is provided below.

CNNs have shown to be useful for categorizing and evaluating diagnoses of skin cancer. Nonetheless, the CNN architecture occasionally has limitations when it comes to image classification. Erroneously labeling skin cancer as benign can have detrimental effects. As a result, we must comprehend all potential causes of the CNN classifier's failure.

[31] photos from the actual global may be intentionally perturbed to fool CNNs into misclassifying. An opposed attack is while an input picture is altered in this sort of manner as to misinform the network into misclassifying it[31]. we will communicate approximately some of those adversarial assaults that would sporadically occur in scientific settings in this article. This studies file carries pertinent information and conclusions [31].

- Changes in color balance
- Changes in the rotation/translation of the input image leading to misclassification of the melanoma as a benign nevus

In order to classify melanomas apart from benign melanocytic nevi, the authors employed a CNN. They improved Inception v3, which had been pre-trained using ISIC 2018 dataset skin lesion image data. They used an FGSM attack, which modifies the blue, green, and red values for each pixel in the input image based on its size. This leads to misclassification, which impacts the final classification [34]. The second attack they carried out was a three-pixel attack, in which they altered just three pixels in the image while leaving the others unaltered. They discovered that this resulted in an effective attack as well. Typically, dermoscopy images are used to train CNNs. Skin pigmentation, photo capture, lighting, and processing all have an impact on color balance. In order to determine whether image color had an impact on the accuracy of classifying skin lesions, they discovered that many melanoma images with variations in RGB colors were incorrectly classified as benign nevuses. By training CNN with different image colors, they also attempted to see if this could be mitigated and discovered a 33 percent drop in the adversarial attack rate. When they retested the images with a little bit more variation, deducting 10 units from the green channel caused a 235 percent rise in false negatives when it came to the diagnosis of melanoma.

In the second test, the rotation of the images was examined to determine whether it could have an impact on the classification accuracy. By permitting arbitrary combinations of rotations up to 360 degrees and translations of up to 50 pixels in both horizontal and vertical directions of the input image with a size of 299 x 299 pixels, they used an evolution-based optimization technique. And they discovered that by simply rotating and translating the image, 45.6% of the test images fooled the classifier into classifying melanoma as a benign nevus. Additionally, they tested the images rotated 180 and 45 degrees, and in both cases there was an 11% increase in the false negative rate.

[32] According to a recent study, the accuracy of CNN classification was also negatively impacted by the presence of blue marker ink in dermoscopic images. [33] A notable variation in the skin classification result was discovered in an empirical investigation of CNN's accuracy in identifying skin cancer. This study found that the type of camera used—a DSLR, an iPhone, or a Samsung—had an impact on the photos' quality and yielded varying outcomes.

6.0 Results and Discussion

A number of the trials that were tested, CNN finished the best accuracy in classifying all other designs. The large-Scale visual recognition opposition (ILSVRC) noticed AlexNet win in 2012, and in 2015, AlexNet, GoogleNet, ResNet, and VGGNet have been the pinnacle 4 competition. The accuracy of skin class with AlexNet changed into 81.8% for [10] as compared to [16, 17]. 83.8% for [16] in comparison. 89.3% for the wide variety [17].

When comparing the findings of [10] and [16], it's possible that [16] obtained greater accuracy because only 150 images—as opposed to 1300 images of 10 different types of skin lesions—were used for testing.

[24] and [26] classified skin lesions using ResNet150. This is one of the greatest comparison scenarios because both employed a similar architectural style and a huge number of photos to carry out this classification. 10,015 images from HAM10,000, 120 images from PH2, and 19,398 images from [26] were used in [24]. Both authors were able to obtain accuracy rates of 96 percent for [26] and 98 point 16 percent for [24] using images from public databases. [24] and [26] show eight and twelve distinct types of skin lesions, respectively, in their pictures.

A significant obstacle in this study is the utilization of archives, which primarily comprise skin lesions from individuals with fair skin. As an example, the majority of the images on ISIC are from the USA, Australia, and Europe. CNN needs to be trained to abstract from various skin tones in order to produce accurate classification results for individuals with darker skin tones. And taking into account pictures with dark skin will help achieve this. By feeding the classifiers with clinical data on various age groups, image sizes, genders, and skin types, the quality of the classification can be enhanced.

7.0 Conclusion

Deep learning-based treatments for skin disorders have great promise, including the until unheard-of advantage of sparing dermatologists from their repetitious job and reducing the demand on medical resources. An automated detection approach that is dependable and that physicians with varying levels of experience may employ on a regular basis is necessary since proper detection is a hard task in the diagnostic process.

A wide understanding of engineering, computer technology, medicine, and different fields is important for deep gaining knowledge of, that's an in depth discipline. because the aforementioned fields maintain to development, deep getting to know is growing fast and has drawn hobby from many nations. it is clear that deep mastering for pores and skin disorder identity could be a capability technique within the close to destiny due to extra reachable answers, software program that can quick seize and process big amounts of facts, and hardware which can carry out tasks that humans cannot.

In addition, certain unfavorable aspects must also be taken into account and investigated, such as: B. weaknesses that allow for enemy attacks. We provide accurate results when we take into account negative data as well, as opposed to capturing only positive data, which biases the system and only yields positive results (the same applies vice versa). If more publications considered this, it would be useful to determine how accurate CNN is at categorizing skin lesions.

8.0 Acknowledgement

9.0 References

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