A Survey on Deep Learning Techniques for Skin Cancer Detection

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Abstract - *Cancer is a serious cause of mortality and morbidity all across the world, and skin cancers are the most widespread. Melanocytic nevi, melanoma, benign keratosis-like-lesions, and other kinds of skin malignancies are some of them. There seem to be a number of visual information parallels amongst unique skin lesions like melanoma and nevus, making detection and diagnosis increasingly challenging. This research discusses novel deep learning approaches which are better at detecting skin cancer. The focus of this research is to present a survey and compare multiple algorithms for recognizing skin cancer that can classify specimens into numerous types of classes based on accuracy, sensitivity, and specificity. The datasets containing sample images showing various types of cancer are obtained. It is then given for feature extraction and the results are classified using various deep learning techniques.*

Key Words: **Skin Cancer, Deep Learning, Transfer Learning, Convolutional Neural Network, MobileNet V2**

1. INTRODUCTION

Cancer emerges as a repercussion of abnormal cell proliferation that can spread to other parts of the body. Environmental factors and genetic mutations are also important. Tobacco use, radiation exposure, stress, pollution, and obesity are only a few of the causes of cancer. Among all cancer forms, skin cancer is the most widespread. It is often seen in Caucasian people (i.e. those who have a white complexion). Basal skin cancer (BSC), squamous skin cancer (SSC), and melanoma are the three main kinds of skin cancer. The first two, and several other less prevalent skin malignancies, are alluded to as nonmelanocytic skin cancer (NMSC) [1].

Skin diseases are long-term and can sometimes progress to cancerous tissues. Skin illnesses must be treated as soon as possible in order to prevent their spread and development. Procedures based on imaging techniques to measure the influence of numerous skin diseases are increasingly in high demand. Several skin cancers have symptoms that can require more time to treat since they can grow for months before even being diagnosed [2]. Dermoscopy is one of the most frequent imaging procedures used among dermatologists. It magnifies the surface of the skin lesion, making its structure more evident to the dermatologist for examination. However, because it is entirely dependent on the practitioner's visual acuity and experience, this technique can only be efficiently utilized by trained physicians[3].

Skin disorders may now be diagnosed much more rapidly and correctly because of advances in laser and photonics-based medical technologies. The cost of such a diagnostic, however, is currently limited and costly. Deep learning models perform the categorization process using images and data more efficiently than other models [2]. The primary goal of this work is to compare the performance of the four classifiers CNN, ANN, Transfer Learning, and MobileNet V2 in terms of detecting skin lesions.

We believe that this survey helps researchers to move forward in the field of skin cancer detection techniques The remaining paper is organized as follows. The literature studied about skin cancer detections and deep learning techniques is discussed in section 2. Section 3 consists of the discussion regarding the survey and conclusion is given in section 4.

2. LITERATURE REVIEW

In [1], Janney. J et. al. investigated and compared three supervised learning algorithms ANN, SVM, and Naive Bayes Classifier in their research. The pictures are divided into two categories: Benign and Malignant. Grey Level Co-occurrence Matrix, Texture, and Wavelet features have been used to extract features from the pictures. The collected elements were fed into the classifier algorithms, and performance analysis was calculated based on Accuracy, Sensitivity, and Specificity. SVM has a 71 percent accuracy rate. When compared to Naive Bayes, which has an accuracy of 71 percent, a sensitivity of 90 percent, and a specificity of 56 percent, it has a sensitivity of 70 percent and a specificity of 72 percent. The ANN classifier is determined to be the best of the three, with an accuracy of 89 percent, a sensitivity of 90 percent, and a specificity of 88 percent.

In [3], Naeem et. al. studied specifically about Melanoma skin cancer. They compared a whole bunch of datasets like PH2, ISBI (2016, 2017, 2018 challenges), DermIS, Dermquest, Mednode, and open-access datasets, specifically for melanoma skin cancer, and discovered that when employing deep learning algorithms, sophisticated and composite pre-processing processes such as image resize, crop, and pixel value normalization are not required. They concluded that in the future, the researcher will need to use a larger dataset and fine-tune hyper-parameters to reduce the risk of overfitting. Furthermore, in order to attain high accuracy, CNN must learn to retrieve data from people with dark skin. Age, gender, and race must also be considered in order to attain better results. However, boosting the accuracy rate is still a work in progress.

In [4]. Sanketh et. al. using the convolution neural network algorithm in a deep learning model to detect cancer and distinguish between malignant and benign skin cancer using ISIC data, they discovered that skin cancer is the most common disease today that can be cured effectively with early detection. They developed a solution to detect this contagious cancer earlier and more efficiently and their model detected the condition with 91 percent accuracy, which is more accurate than a skilled dermatologist, but they used fewer epochs due to a lack of hardware resources. Increasing the number of epochs and the number of transitions each epoch, they could have improved its efficiency.

In [5], Daghrir et. al. experimented on a public dataset ISIC which has around 23000 images but only 640 were chosen by them. They compared 3 algorithms namely CNN, SVM, and KNN. Using only the five closest neighbors, they obtained the lowest accuracy. Because it is sensitive to outliers, KNN can only detect malignant skin lesions with difficulty. However, due to its efficiency and versatility, the SVM classifier outperforms the KNN classifier. Despite the fact that an SVM classifier performed admirably, the CNN is still regarded as a more strong and robust technique for detecting melanoma skin cancer.

In [6], Ashraf et. al. extracted only discriminative features using the proposed system's Region of Interest-based images. Original photos, as well as ROIs for both DermIS and DermQuest, were used in their tests. The sample images for training in these datasets had concerns with class imbalance. So they used a combination of transfer learning and significant augmentation techniques to solve this challenge. They transferred the AlexNet model's initial low-level feature layers and determined that ROI with augmentation produces the best outcomes when compared to the original and non-augmentation techniques.

In [7], Hosny et. al. used the PH2 dataset to train and evaluate their proposed model. They evaluated their proposed model's performance using the well-known quantitative metrics of accuracy, sensitivity, specificity, and precision, and obtained the results of 98.61 percent, 98.33 percent, 98.93 percent, and 97.73 percent, respectively.

In [8] Vidya and Karki worked on SVM, KNN, and Naive Bayes. They downloaded 328 photos of benign skin lesions and 672 images of melanoma for their project from the International Skin Imaging Collaboration (ISIC). Using SVM classifiers, they got classification results with 97.8% accuracy and 0.94 area under the curve. Furthermore, while employing KNN, the sensitivity they achieved was 86.2 percent and the Specificity was 85 percent.

In [10], Roffman et. al. retrieved parameters like gender, age, BMI, diabetes status, smoking status, emphysema, asthma, race, Hispanic ethnicity, hypertension, heart illnesses, rigorous exercise habits, and stroke history for their NN. The area under the ROC curve for training and validation in this investigation was 0.81 and 0.81, respectively. Their findings (training sensitivity 88.5 percent and specificity 62.2 percent, validation sensitivity 86.2 percent, and specificity 62.7 percent) were comparable to those of a recent study of basal and squamous cell carcinoma prediction that incorporated UVR exposure and family history data.

In [11], Sae-Lim et. al. used the official dataset of Human Against Machine (HAM 10000) for the evaluation of their model, which was a collection of multi-source dermatoscopic images. In order to improve the efficiency of the classifier, they employed data upsampling and data augmentation methods. The comparative findings revealed that their modified model outperformed the traditional MobileNet in terms of accuracy, specificity, sensitivity, and F1–score.

In [13], Mahbod et. al. have shown that pre-trained deep learning models, which have been trained for natural image classification, may also be used to classify dermoscopic images. Furthermore, they concluded that combining deep features from different layers of the same network or from several pre-trained CNNs improved classification performance. Overall, excellent classification results were exhibited on the difficult images of the ISIC 2017 competition, and future work combining more deep information from more CNNs could potentially lead to even better predictive models.

In [14], Khan et. al. experimented on an existing saliency method to improve the suggested OCF approach even further. They used a new pixel-based fusion method is used for their project. This stage addressed the issues of uneven lesion shape, texture, and size, as well as the presence of a lesion on the border region. Second, for deep feature extraction, a DCNN-9 architecture was proposed by them, and then parallel fusion-based color features are fused. Finally, a selection technique was proposed in order to significantly reduce the execution time and improve the overall accuracy of our model. Their suggested method was put to the test on three well-known datasets, including ISBI 2016, ISBI 2017, and ISBI 2018, and it performed well.

In [15], Zhang et. al. boosted the efficiency yield of CNN by using an updated version of the whale optimization method. They used the optimization technique to find the best weights and biases in the network in order to reduce the difference between the network output and the desired output. Their suggested technique's performance was evaluated using two distinct benchmarks, Dermquest and DermIS, and the results were compared to ten different methods, including the semi-supervised method, Spot-mole tool, AlexNet, Ordinary CNN, VGG-16, LIN, Inception-v3, and ResNet. Specificity, accuracy, sensitivity, NPV, and PPV are the performance indicators used here.

Table -1: Skin Cancer Detection Techniques Comparison

Author and Year	Type of Cancer	Techniques Used
Naeem et. al. 2020 [3]	Melanoma	CNN
Sanketh et. al. 2020 [4]	Melanoma	CNN
Daghrir et. al. 2020 [5]	Melanoma	KNN, SVM, CNN
Ashraf et. al. 2020 [6]	Melanoma	CNN based Transfer Learning
Hosny et. al. 2018 [7]	Melanoma	Transfer Learning
Vidya and Karki 2020 [8]	Benign and Melanoma	SVM, KNN, and Naive Bayes
DeVries and Ramachandram 2017 [9]	Melanoma, Seborrheic Keratosis	ImageNet pre-trained Inception-v3
Roffman et.al. 2018 [10]	Non-Melanoma (NMSC)	ANN
Mahbod et. al. 2019 [13]	Melanoma, Seborrheic Keratosis, Benign Nevi	AlexNet, VGG-16, ResNet 18 along with SVM
Zhang et. al. 2019 [15]	Melanoma	CNN using Whale Optimization
Jamil et. al. 2019 [17]	Melanoma	Colour Model Segmentation
Jadhav et. al. 2019 [18]	Melanoma	CNN and SVM
Khan et. al. 2019 [20]	Melanoma and Nevus	SVM

3. DISCUSSION

There are many skin cancers out there like Melanoma, Nevus, Benign Nevi etc. Out of which, Melanoma is the most common and malignant type of skin cancer. From table 1, we conclude that CNN is the most used classifier as it generates some of the best accuracy results.

Also many of the researchers have detected only one type of skin cancer i.e. Melanoma. Researchers also should go for other skin cancers which are equally important to detect like Basal cell carcinoma, Melanocytic Nevi, Vascular lesions, Dermatofibroma, etc. which will allow the classifier to work more efficiently and detect numerous types of skin cancers.

Also many of the researchers have not deployed it on some mobile app or a website so that patients can check the type of skin cancer with ease and at home itself. Nowadays it's really essential to have things connected to the internet for fast retrieval of information. Skin cancers like melanoma are really deadly and hence connecting these models to the internet through a website or an app is really necessary as it can be a major factor between life and death.

4. CONCLUSION

In this paper, we reviewed different skin cancer detection techniques. We classified these detection techniques based on different types of Deep learning models like CNN, SVM, KNN etc. Different types of skin cancers were discussed in this paper. Limitations and future direction of skin cancer detection techniques were also discussed. We believe that this survey work will help researchers to understand the deep learning techniques, current trends, challenges, and future scope of skin cancer detection.

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