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RESEARCH ARTICLE

A REVIEW ON MELANOMA SKIN CANCER CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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Abstract – Melanoma is the most dangerous form of skin cancer and is responsible for more than 70 percent of skin cancer deaths. Melanomas develop from malignant melanocytes. Based on the years lost to cancer, melanoma would merit a higher ranking because relatively young people are affected by this malignancy. Melanoma is usually diagnosed in patients of a relatively young age; overall, the total number of patients suffering from melanoma is accumulating. The automated computerized diagnosis mechanism helps to improve the accurate analysis of skin cancer which helps the dermatologists to accelerate the diagnostic time and improve the better treatment for the patients. Detecting melanoma skin cancer using CNN involves leveraging deep learning techniques to automatically extract and learn hierarchical features from dermoscopic images. CNNs process input images through multiple convolutional layers, capturing essential patterns such as texture, shape, and color variations indicative of melanoma. Pretrained models like SVM, ResNet, U-Net and YOLO are often used to enhance accuracy through transfer learning. YOLO, SVM, CNN, ResNet, U-net and MobileNetv3 network are employs dataset for the detection of skin cancer with 96.46%, 90.35%, 91.23%, 97.87% of success rate respectively.

Keywords *– Skin cancer, CNN, SVM, ResNet, YOLO.*

1. INTRODUCTION

Skin cancer is a major health issue in the present day especially melanoma skin cancer. Melanoma is a type of cancer which starts, in almost all cases, in pigment cells (melanocytes) causing in general dark lesion [1]. However, in some cases, the lesion can be pink, white or tan. Besides coloration, we can find several other characteristics of melanomas like the texture and the structures of the lesion which differentiate them from benign lesions. Melanoma is considered the deadliest type of skin cancers [2]. The American Cancer Society (ACS) estimates that about 91,270 novel cases of melanomas are diagnosed (55,150 men and 36,120 women) in 2018 [3]. In the same year, according to the ACS estimated about 9,320 fatalities. Melanoma is a particularly deadly form of skin cancer and although it accounts for only 4% of all skin cancers it is responsible for 75% of all skin cancer deaths [4]. If melanoma is diagnosed and treated in its early stages, it can be cured but if the diagnosis becomes late, melanoma can grow deeper into the skin and spread to other parts of the body [5].

The growth of skin cancer is rapidly increased. Melanoma skin cancer image is diagnosed visually using dermoscopy by the dermatologist [6]. The experienced dermatologist can diagnosis the image by observation of one of the most techniques called ABCD rule. The characteristics of ABCD rule are A – Asymmetry, B – Border irregularity, C – Color distribution, D – Diameter Length [7]. The growth of skin cancer cells may outspread into organs and tissues. Dermoscopy technique is a non-invasive imaging method that is used to detect melanoma skin diseases. Generally, skin cancer disease is diagnosed by the expert dermatologist (Skin specialist doctor) [8]. The dermatologists can diagnose skin cancer diseases by visually screening the dermoscopy images. Based on his experience he can diagnose the type of skin cancer but it is not a 100% guarantee to detect skin cancer and sometimes it may lead to potential harm. Here potential harm means, the unnecessary procedure has been performed such as collecting the skin biopsy for lesions, sometimes these biopsy results do not turn out as skin cancer [9]. Early detection of skin cancer leads to a decrease in the death rate and also accelerate the diagnostic time to improve the better treatment for the patient [10]. The study main objective is described as follows:

The study is organized as follows: Chapter II presents an analysis of Skin cancer, while Chapter III explores CNN architectures, specifically ResNet, U-Net, and MobileNet. Chapter IV provides a discussion of the survey results and Chapter V concludes the study.

2. STUDY ON MELANOMA SKIN CANCER DETECTION

In recent years, numerous studies have investigated the melanoma skin cancer with DL and ML methods. The following section provides a brief overview of some recent research works.

Support Vector Machine

In 2021 Banasode, P., et al [11] suggested a machine learning based technique for skin cancer detection it can be a helpful factor in the medical field. The major causes of skin cancer are air pollution, UV radiation, unhealthy life style etc. The concept of machine learning will be used to determine the disease and help us to detect the result. The most commonly used classification algorithms is support vector machine (SVM). The result of this study will help doctors to treat disease at the initial stage and further aggravation can be avoided.

In 2021 Ojukwu, C.E., et al [12] suggested two machine learning models are built using support vector machines and convolutional neural networks to detect malignant melanoma skin cancer. An open-source dataset of seven hundred malignant and benign skin cancer images was downloaded from the Kaggle website. Eighty percent of the dataset was used for training the models while twenty percent of the dataset was used for testing the models. The goal of this paper is to train two models using the same dataset, hardware specifications, and software environment to ascertain the individual accuracies of the models in skin cancer detection and foster a fair comparison.

CNN

In 2021 Dildar, M., et al [13] suggested a various neural network techniques for skin cancer detection and classification. Skin cancer detection requires multiple stages, such as preprocessing and image segmentation, followed by feature extraction and classification. This review focused on ANNs, CNNs, KNNs, and RBFNs for classification of lesion images. CNN gives better results than other types of a neural networks when classifying image data because it is more closely related to computer vision than others

In 2021 Vargas, D.P.M., et al [14] developed an embedded system with raspberry Pi 3 B+ with a generic camera and implemented the CNN described for the classification of skin cancer. Deep Learning reaches elevated accuracy levels in image classification tasks and is set to become a reliable solution for medical image classification. In this research, used these DNN advantages to build a convolutional neural network (CNN) trained with open-source databases to the classification of skin lesions benign and malignant. The results of this research contribute to the state of art regarding Deep learning applied to the development of medical applications.

ResNet

In 2021 Sharma, M., et al [15] suggested a residual neural network (ResNet) for the Detection and Diagnosis of Skin Diseases. These diseases have a potential to become extremely dangerous if they are not treated in the nascent stages. It is extremely important that skin diseases are detected and diagnosed at the starting stages so that serious risks to life are avoided. It achieved an accuracy of 95% using ResNet for training of the model and prediction of results at an epoch value of 10.

U-Net

In 2021 Li,W., et al., [16] had introduced a deep learning-based U-Net and image inpainting framework for DHR. During the segmentation process, a well-labeled dataset was formed and utilized to train the U-Net for generating exact hair masks. SN-Patch GAN is a free-form image inpainting framework used for inpainting hair gaps. The assessment technique was used to assess the impact of DHR in terms of single dermoscopy image, and it was repetitive until there was no variation in the intra-SSIM score.

Res-Unet

In 2020 Zafar., et al., [17] devised a deep learning-based Res-Unet that incorporates with ResNet and UNet for segmenting lesion boundaries. Additionally, hair removal was performed by image inpainting, which considerably enhanced the segmentation fallouts. The suggested Res-Unet was trained on the ISIC 2017 dataset and tested on both ISIC 2017 and PH2 dataset. The Res-Unet achieves the Jaccard Index of 0.77 on the ISIC 2017 and 0.85 on the PH2 dataset.

Mobile Net

In 2024 Zakariah, M., et al [18] proposes a novel approach to tackle the issue by introducing a method for detecting skin cancer that uses MixNets to enhance diagnosis and leverages mobile network-based transfer learning. The present study utilizes the ISIC dataset, comprising a validation set of 660 images and a training set of 2637 images. The results demonstrate impressive performance metrics, with MobileNet and MixNets models, and the proposed approach achieves an outstanding accuracy rate of 99.58%.

YOLO

In 2019 Unver., et al., [19] introduced deep learning-based YOLO and Grabcut algorithm for segmenting the skin lesions in dermoscopic images. This method performs lesion segmentation in four phases: Exclusion of hairs on the lesion, Identifying the area of lesion, Segmentation of the skin lesion area, and post-processing with morphological operations. The proposed pipeline model achieved 93.3% of accuracy on ISBI 2017 dataset.

In 2023 Aishwarya, N., et al [20] suggested a yolo based deep neural network for classifying nine types of skin cancer. In the testing phase, the given image is basically divided into equally sized blocks and each block is compared with the trained labelled image blocks to classify the type of cancer. The results of the proposed work can be improved by incorporating larger datasets for each type of cancer which will aid for better clinical investigation.

3. MATERIALS AND METHODS

DL models for Skin cancer detection have developed the field of dermatology by offering powerful tools for early analysis and classification of skin cancer. These models primarily rely on CNN, a class of DL architectures ideally suited for image analysis. CNNs can automatically identify key structures in Skin cancer images, making them highly effective at differentiating between the presence and absence of cancer.

The DL models for identifying skin cancer provide details about some CNN variations, including Alex Net, ResNet, Google Net, Mobile Net, U-Net and GAN. Advanced networks that can accommodate different resource limits and scalability requirements include Alex Net, ResNet, Google Net, Mobile Net, U-Net and GAN.

ResNet

ResNet, developed by Kaiming and his team at Microsoft Research in 2015, allows for the training of very deep neural networks through residual connections. These connections allow certain layers to be bypassed, helping gradients flow during training and overcoming the vanishing gradient problem. Models such as ResNet-50, ResNet-101, and ResNet-152 demonstrate that deep networks can achieve high accuracy in tasks such as image recognition and segmentation.

Support Vector Machine (SVM)

SVM is a powerful supervised learning algorithm developed by Vladimir Vapnik and his colleagues at AT&T Bell Laboratories in the 1990s. It is based on the principle of finding an optimal hyperplane that maximizes the margin between different classes in a dataset. SVM is particularly effective in high-dimensional spaces and works well with both linear and non-linear classification problems by using kernel functions like polynomial, radial basis function (RBF), and sigmoid. The core idea is to transform data into a higher-dimensional space where it becomes easier to separate classes, making it highly efficient for complex classification tasks.

CNN

CNN are a class of deep learning models primarily designed for image processing and pattern recognition. The concept of CNNs was first introduced in the 1980s by Yann LeCun, but they gained significant attention in the 1990s with the development of LeNet-5, a CNN model designed for handwritten digit recognition. However, the true breakthrough came in 2012 when AlexNet, developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, won the ImageNet competition by a large margin, demonstrating the immense potential of CNNs in computer vision tasks. Since then, CNNs have evolved with architectures like VGGNet, ResNet, and EfficientNet, making them a cornerstone of deep learning in various domains.

Mobile Net

Mobile Net uses depth-wise separable convolutions in its layers, which are made up of point-wise (PC) and depth-wise convolutions (DWC). In DWC, the channels of the input tensor are filtered independently, reducing computations, whereas in PC, the results are combined. This plan decreases the quantity of constraints and computations compared to traditional convolutional layers, making Mobile Net suitable for embedded and mobile applications with limited computational resources. The MobileNet detect the ski disease in humans with high reliability rate utilizing Kaggle dataset at 99.75% of success rate.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The methodologies for classifying and identifying skin cancer are briefly compared in the section below.

4.1. Experimental Results

In this section, a DL approaches for detecting skin cancer is mentioned and discussed. The pre-process models and various datasets that were utilized to identify skin cancer are discussed. When contrasted with the models given below, MobileNetv3 model performs well and beats other models with 99.75% reliability. Table 1 below displays a comparison of various methods for detecting skin cancer.

Author& year	Dataset	Data description	Pre-processing methods	Network model	Partitioning	Validation results
Unver., et al., 2019 [19]	ISBI 2017 dataset	includes a total of 2,750 image	min-max normalization and data augmentation	YOLO	achieved 90% training and 86% IOU rates	achieved a accuracy 90%
Banasode, P., et al 2021 [11]	ISIC dataset	ISIC dataset contains 217 Images	precaution to be taken at an early stage	SVM	training (80%), validation (10%), and testing (10%).	Accuracy (91.23%)
Ojukwu, C.E., et al 2021 [12]	Kaggle dataset	It includes 397 skin cancer images	detect malignant melanoma skin cancer.	SVM	80%dataset was for training the models	Accuracy (90.35%)
Dildar, M., et al 2021 [13]	ISIC dataset	397 cancer images	More curable in initial stages	CNN	high 95% for training	Accuracy (96.46%)
Vargas, D.P.M., et al 2021 [14]	HAM10000	486 images	Increase patient life quality	CNN	100 training images	Accuracy (93.21%)

Sharma, M., et al 2021 [15]	DERM NET.	589 cancer images	Serious risks to life are avoided	ResNet	50 for training and 50 for testing	Accuracy 95%
Li, W., et al 2021 [16]	ISIC dataset	ISIC dataset contains 217 Images	Important information of the skin lesion	U-Net	70 to 30 in terms of training to testing images,	Accuracy (97.87%)
Zafar., et al., 2020 [17]	ISIC 2017	Contains 10,288 images	Analysis and segmentation of lesion	Res-Unet	training (80%), validation (10%) and testing (10%)	Accuracy (93.30)
Zakariah, M., 2024 [18]	ISIC dataset	Contains 10,288 images	Enhance diagnosis and leverages	MobileNet	Validation set of 660 images and a training set of 2637 images.	Accuracy rate of 99.58%.
Aishwarya, N. 2023 [19]	ISBI 2017 dataset	4389 images	Real time environment in terms of detection	YOLO	1502 images for training and 100 images for the testing	Accuracy (96%)

YOLO, SVM, CNN, ResNet, U-net and MobileNetv network are employs dataset for the detection of skin cancer with 96.46%, 90.35%, 91.23%, 97.87% of success rate respectively.

5. CONCLUSION

The paper presents a survey of the research work about recognition and detection of Melanoma skin cancer using DL methods presented over the period from 2019 to 2024. This work supports the concept that DL algorithms to enhance the approaches for detecting Melanoma skin cancer. A DL model analyzes complex visual data using neural networks, and it provides an effective and scalable solution to skin cancer. Among the models evaluated, MobileNet achieved the highest reliability, with a success rate of 99.75%, showcasing its efficiency in skin cancer detection. The findings emphasize the importance of deep learning in medical imaging and suggest further advancements through the integration of larger datasets and optimization techniques to enhance diagnostic precision. YOLO, SVM, CNN, ResNet, U-net] and MobileNetv3 network are employs dataset for the detection of skin cancer with 96.46%, 90.35%, 91.23%, 97.87% of success rate respectively.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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