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A Comprehensive Joint Learning System to Detect Skin Cancer

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ABSTRACT: Deep learning algorithm-based algorithms are developed to assist dermatologists in the timely and accurate diagnosis of skin cancers with the end goal of developing an AI-powered device that can detect skin cancers in real time. We discussed different deep learning architectures used for the detection of skin cancers, and we specifically focused on skin cancer classification using deep learning algorithms. This survey paper compared the performance and computational cost of different deep learning methods covered in this paper. The size of the datasets limits the performance of deep learning algorithms in skin cancer detection; we do not have large skin lesion datasets. Moreover, most skin lesion datasets have white skin images; the deep learning algorithms' accuracy will decrease when we test the deep learning models on different skin colors. In the future, data can be collected with varying colors of skin to address the color bias in skin lesion datasets. Moreover, to assist the dermatologist in real-time, there is a need to work on the hardware implementation of deep learning algorithms.

KEYWORDS: skin cancer; segmentation; classification; deep learning

I.INTRODUCTION

Skin cancer is one of the most common types of cancer that begins with the uncontrolled reproduction of skin cells. It can occur because of the ultraviolet radiation from sunshine or tanning beds, and it causes skin cells to multiply and form malignant tumors.

Skin cancer is one of the primary reasons for deaths worldwide. According to statistics published by [**1**], 97,160 Americans were diagnosed with skin cancer in 2023, which is 5.0% of the total cancer cases reported in the United States, and 7990 people died because of skin cancer which is 1.3% of the total deaths because of skin cancer in the United States [**1**]. Melanoma is one of the most common and dangerous types of skin cancer that can spread quickly to other body parts. Approximately 21 out of 100,000 melanoma cases were diagnosed in the United States between 2016 and 2020. The death rate because of melanoma was 2.1 per 100,000 diagnosed cases, and 1,413,976 people were living with melanoma in 2020 [**1**]. The five-year survival rate of skin melanoma is 93.5% which is relatively high [**1**]. The five-year survival rate is 99.6% when skin melanoma is diagnosed at an early stage [**1**]. There are more chances of survival when skin melanoma is localized, which means it does not spread to other body parts, but only 77.6% of skin melanomas are diagnosed at the local stage. The number of deaths because of skin melanoma can be reduced if it is detected at its early stages.

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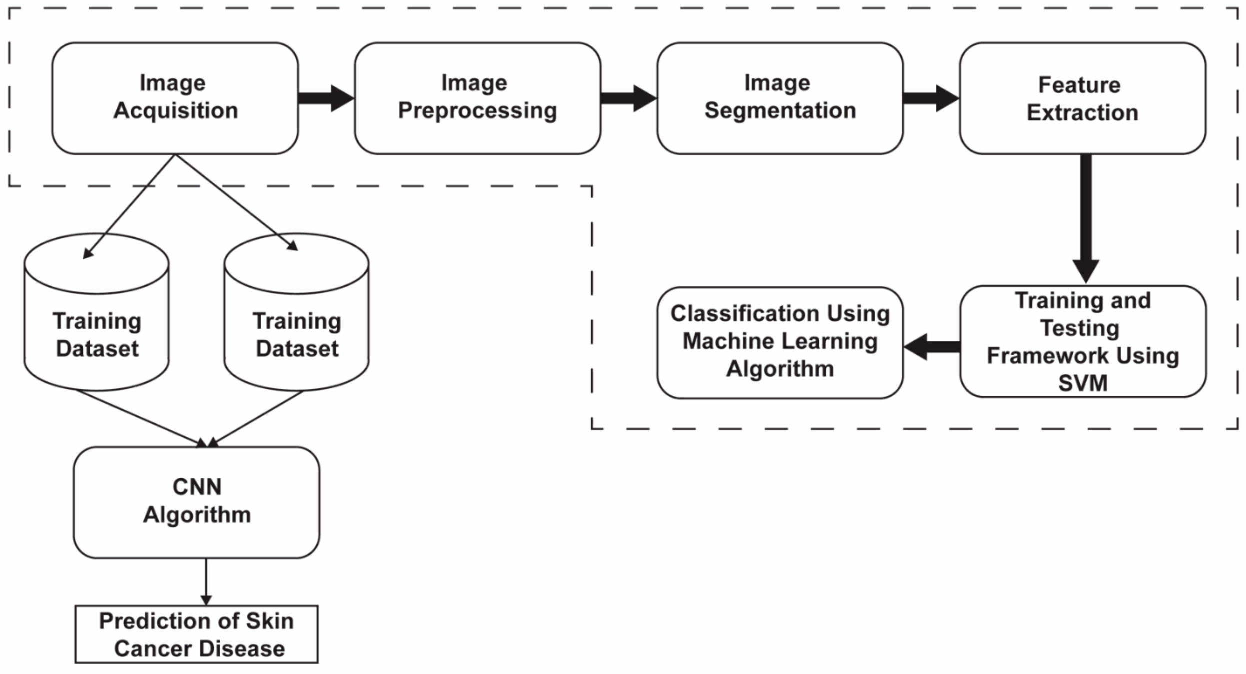

Fig 1: Skin Diagnostics

The most common method of diagnosing skin cancer is by visual examinations by dermatologists, which has an accuracy of about 60% [**2**]. The diagnostic accuracy of skin cancers increases to 89% by using dermoscopy. We also want to diagnose skin cancers with high sensitivity; dermoscopy has a sensitivity of 82.6% for detecting melanocytic lesions, 98.6% for basal cell carcinoma, and 86.5% for squamous cell carcinoma [**3**]. Dermoscopy increases the accuracy of melanoma diagnosis, but it may still be challenging to diagnose some lesions, particularly early melanomas accurately, that lack distinctive dermoscopic features. Though dermoscopy diagnoses skin melanoma with very good accuracy, it is not well suited for diagnosing featureless melanoma, and there is still a need to improve accuracy further to increase the survival rate of patients. The problems with dermoscopy and the need to increase the diagnostic accuracy of skin cancer further laid the foundation for developing computer-aided detection methods for diagnosing skin cancers.

Generally, there are five steps in computer-aided skin cancer diagnosis: image acquisition, pre-processing, segmentation, feature extraction, and classification [**4**,**5**]. The most essential steps in computer-aided diagnosis of skin cancers are segmentation and classification [**6**,**7**]. However, diagnosing skin cancer using computer-aided methods is not straightforward, and we must consider many factors for an accurate diagnosis. For example, artifacts such as hairs, dark corners, water bubbles, marker signs, ink marks, and ruler signs, as shown in **Figure 1** [**6**,**8**,**9**] can result in misclassification and inaccurate segmentation of skin lesions.

II.RELATED WORK

lenezi et al. [**33**] presented a dilation, normalization, and pooling-based approach for removing hairs from skin lesion images. Alenezi et al. [**33**] used the relief feature selection to select features extracted using ResNet-101 to train the SVM classifier to classify melanoma. Alenezi et al. [**33**] also trained SVM on features extracted using AlexNet, DarkNet19 [**34**], GoogleNet [**25**], SqueezeNet [**35**], Xception [**36**], and MobileNetV2 [**37**], with SVM giving the best accuracy of 96.15% and 97.15% on ISIC 2019 and ISIC 2020 with features extracted using ResNet-101 [**20**]. Dataset 1 only contained 1168 images. Deep architectures such as ResNet-101 were used for feature extraction, which may result in overfitting as it was trained on very small dataset; the proposed work has limitations in terms of the time required for the parameter selection of the SVM classifier.

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Abbas and Gul [**38**] proposed a NASNet-based approach [**39**] for classifying melanoma images on the ISIC 2020 dataset. Abbas and Gul [**38**] used geometric transformations to perform data augmentation to improve classification performance. The proposed algorithm achieved an accuracy of 97.7% and an F1-score of 0.97.

Gouda et al. [**40**] used ESRGAN [**41**] for generating synthetic images to increase the dataset size for training the CNN network to classify skin lesion images. The CNN network trained on ISIC 2018 dataset achieved an accuracy of 83.2%, comparable to the performance of more complex networks such as Resnet-50, InceptionV3, and Inception ResNet [**42**]. The proposed work was tested on a small dataset using 3533 images from ISIC 2018. The best classification accuracy of 0.8576 was obtained using Inception50, which is still low. The main goal of using machine learning/deep learning in skin cancer classification is to improve the diagnostic accuracy of skin cancers, but the accuracy achieved using this method was low compared to dermoscopy.

Alwakid et al. [**43**] proposed using ESRGAN and segmentation as a pre-processing step to improve the classification performance on skin lesion datasets; ESRGAN was used for enhancing the image quality, and segmentation was used to extract a region of interest (ROI) from skin lesion images. Data augmentation was also performed using the synthetic skin lesion images generated by ESRGAN. CNN network trained using the proposed approach achieved an accuracy of F1-score of 0.859, whereas the ResNet-50 model achieved an F1-score of 0.852; both networks were trained on the HAM10000 dataset.

Bassel et al. [**44**] proposed a hybrid deep learning approach based on the Stacked CV method trained on the ISIC 2019 for classifying skin cancer. Bassel et al. [**44**] trained proposed Stacked CV method in three levels by deep learning, SVM [**45**], RF [**46**], NN [**47**], KNN [**48**], and logistic regression methods as shown in **Figure 10**. Bassel et al. [**44**] used three modes of feature extraction, i.e., Resnet50, Xception, and VGG 16, from which Xception achieved high accuracy of 90.9% accuracy F1-Score is 0.89. The proposed model was trained and tested on a small dataset consisting of 2637 training images and 660 test images. The model may not perform well on large datasets as it will have limited generalizability because a very small dataset was used for training. Deep models used increases the computational cost of training these networks.

ashid et al. [**62**] proposed a MobileNetV2-based transfer learning algorithm for classifying skin melanoma trained on the ISIC 2020 dataset. Rashid et al. [**62**] used data augmentation to address the problem of class imbalance and achieved an average accuracy of 92.8%. The proposed model should be evaluated on a multi-class classification problem as it was tested only for the malignant versus benign case. Aljohani and Turki [**63**] evaluated six deep learning models, DenseNet201, MobileNetV2, ResNet50V2 [**54**], ResNet152V2, Xception, VGG16, VGG19, and GoogleNet for skin cancer classification. Aljohani and Turki [**63**] trained all models on 7164 images from ISIC 2019 dataset. The maximum test accuracy of 76.09% was achieved using GoogleNet, which was quite low, and the model was tested only for the binary classification case. Bian et al. [**64**] presented a method for skin cancer classification by combining deep learning and medical domain knowledge. An extension-dependent function in extension theory is used to detect the Blue White Veil (BWV) feature, which is very important in diagnosing melanoma. YOLOv3, optimized by Dynamic Convolution Kernel (YoDyCK) trained on ISBI 2016, was used to classify skin cancer, which achieved maximum accuracy of 96.2%. Most skin cancer datasets were curated from the images collected from Western countries with fair skin. Deep learning models trained on images collected from Western countries will not perform well when tested on images with darker skin because of the dataset bias. This work addressed the problem of bias in skin lesion datasets by training the proposed model on images collected from Asian countries. Demir et al. [**65**] classified skin lesion images into two categories, benign and melanoma. The classification was performed using ResNet-101 and Inception-v3 trained on the ISIC archive. Accuracy of 84.09% and 87.42% was achieved using ResNet-101 and Inception-v3, respectively.

III.METHODS

Convolutional neural networks learn directly from data and are widely used for image recognition and classification. CNNs have been considered one of the best machine learning algorithms to analyze grid-like structured data, such as images. CNNs have shown exceptional performance in image processing problems and computer vision tasks such as localization and segmentation, classification, and detection [**15**]. A convolutional neural network typically contains tens or hundreds of layers, each of which can be trained to recognize distinct aspects of an image. The output of each convolved picture is utilized as the input to the following layer after filters are applied while training an image with various resolutions. The filters start with detecting basic features such as brightness and edges and become more complex until they reach features that specifically identify the object [**15**]. There are several hidden layers between a CNN's input

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and output layers. These layers carry out operations that alter the data to learn features specific to the data. Convolution, activation (or ReLU), and pooling are the most used layers. The Conv layer is a Convolutional Network's core building block that does most of the computational heavy lifting. With convolution, convolutional filters are applied to the input images, activating different aspects of the images. By setting negative values to zero and keeping positive values constant, an activation function facilitates faster and more effective training because only the activated characteristics are carried over to the following layer; this is frequently referred to as activation. Pooling reduces the number of parameters the network needs to learn by conducting nonlinear downsampling on the output. Over tens or hundreds of layers, these operations are repeated while each layer learns to recognize various features. The output for the final classification is provided by a classification layer in the CNN architecture's top layer.

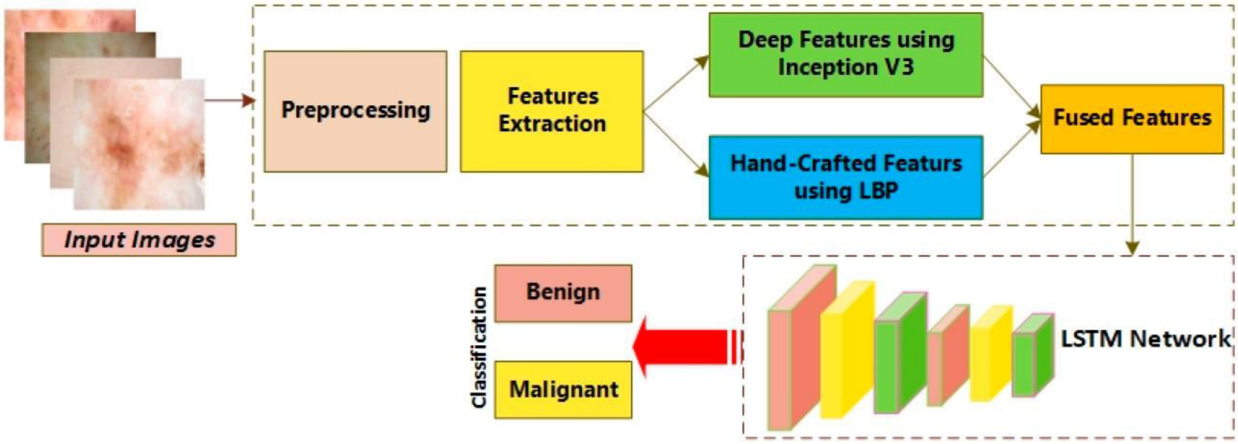

Fig 2: Work Flow

AlexNet won an ImageNet 2012 competition consisting of eight layers. In deep learning, more layers are added to improve performance and minimize the error rate. Adding more layers results in a vanishing gradient in which the gradient becomes zero and exploding gradient in which the gradient becomes too large. He et al. [20] solved the problem of exploding and vanishing gradients by introducing a concept of skip connections. The skip connection bypasses some levels in between to link layer activations to subsequent layers to make residual blocks stacked together to create a ResNet architecture. The layer causing a problem during training can be skipped avoiding exploding and vanishing gradients, and helps train deep neural networks.

IV.RESULT ANALYSIS

Actinic keratoses (AKs) are the scaly, dry skin lesions some people experience. An AK is not skin cancer, although it results from too much sun. An AK is a pre-malignant skin growth that has the potential to develop into the typical kind of skin cancer known as squamous cell carcinoma. AKs typically develop on exposed skin, which includes the head, neck, hands, and forearms. Treatment is essential for AKs because they can grow into a specific type of skin cancer shows common types of skin cancers.

SCC is also the most prevalent type of skin cancer. SCC is more likely to occur in those with light skin, but darker-skinned individuals can also develop this skin cancer. The appearance of SCC is frequently a red, firm lump, a scaly area, or a sore that cures and reopens. Skin that has frequent sun exposure, such as the rim of the ear, the face, neck, arms, chest, and back, is more prone to developing SCC. SCC can penetrate the skin deeply, resulting in harm and disfigurement. Early detection and treatment of SCC can stop it from developing deep and spreading to other body parts.

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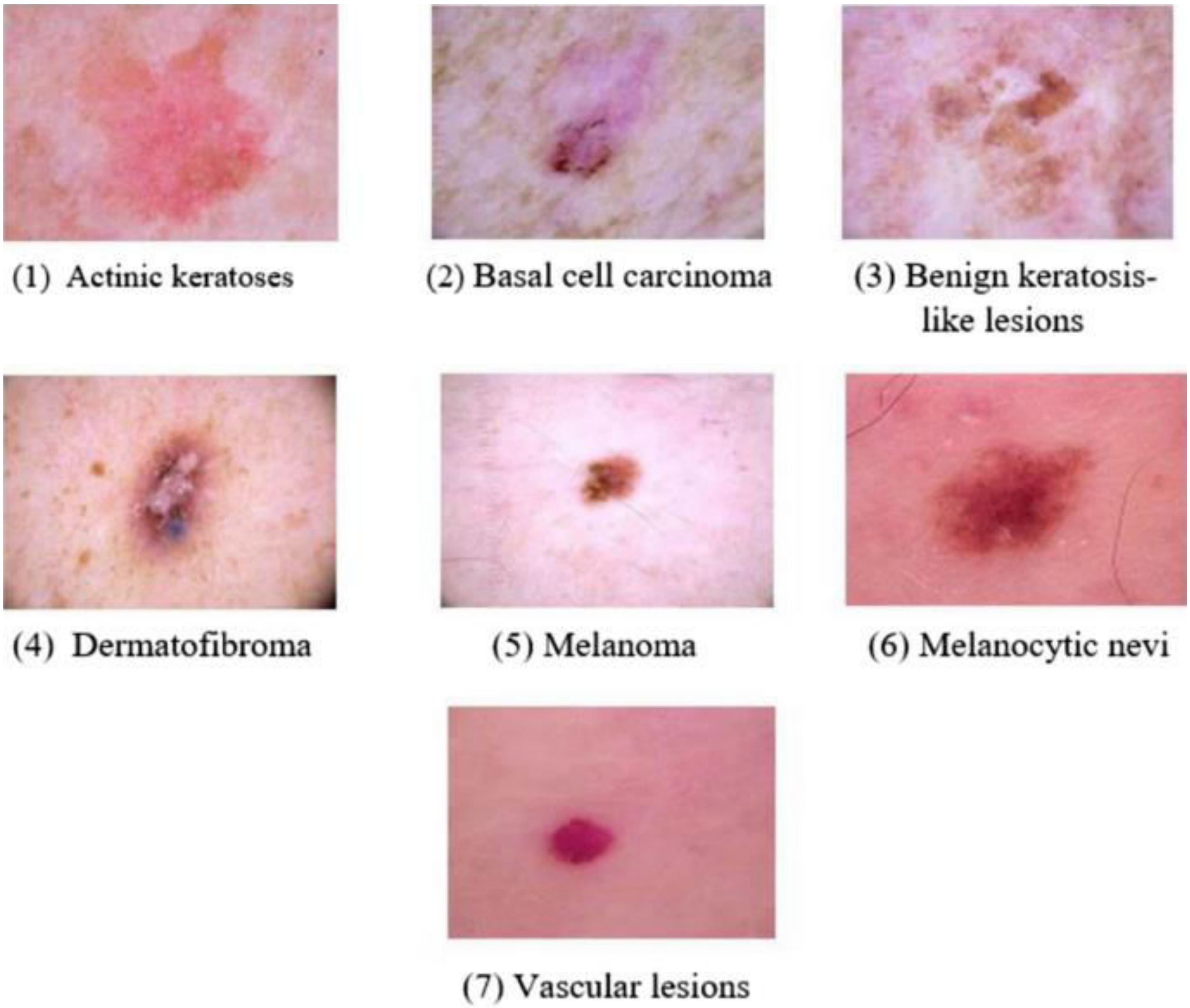

Fig 3: Result Analysis

The Internet of Things (IoT) uses connected devices and sensors, like high-resolution cameras and specific sensors in wearable devices, for the collection of skin images with abnormalities. Skin cancer detection is difficult because of differences in lesion size, shape, and lighting conditions. To address this, an innovative approach called “ODL-SCDC”, combining deep learning with IoT technology, is developed. The proposed model uses advanced techniques like hyperparameter selection and feature extraction to improve skin cancer classification. The results show that ODL-SCDC outperforms other methods in accurately identifying skin lesions, which could have a significant impact on early cancer detection in the medical field.

V.CONCLUSION

Skin cancer is one the most dangerous types of cancer and is one of the primary causes of death worldwide. The number of deaths can be reduced if skin cancer is diagnosed early. Skin cancer is mostly diagnosed using visual inspection, which is less accurate. Deep-learning-based methods have been proposed to assist dermatologists in the early and accurate diagnosis of skin cancers. This survey reviewed the most recent research articles on skin cancer classification using deep learning methods. We also provided an overview of the most common deep-learning models and datasets used for skin cancer classification.

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