**Optimized Ensemble Highest Ranking-based Trio-phased Intelligent Skin Cancer Detection: Contribution of Deep Learning**

**Introduction**

Different types of cancer may exist in the human body and skin cancer is one of the top three perilous types of cancer caused by damaged Deoxyribonucleic Acid (DNA) that can cause death [9]. It is provoked by some factors like smoking, alcohol usage, allergies, infections, viruses, physical activity, environmental change, exposure to Ultra Violet (UV) light, and so on [10]. This damaged DNA begins cells to grow uncontrollably and nowadays it is getting increased speedily. The skin on the body provides a shield of protection against electronic, chemical, and physical injuries [11]. It defends us from diseases and pollutants, avoids moisture loss due to the presence of intercellular lipids in their hydrophilic area that captures water molecules [12]. Because of the pigment melanin which absorbs UV radiation, the skin has the ability to reduce the harmful effects of UV radiation. The skin comprises three types of layers known as epidermis, dermis, and hypodermis [13]. The outermost layer, epidermis shields the skin from the surroundings. Underneath the epidermis, there's a layer known as the dermis that includes strong connective tissue and glands of sweat. The hypodermis is a subcutaneous layer that lies beneath the dermis and is mostly made up of fat [14]. Unique cells in the epidermis called melanocytes form the color of the skin and generate the pigment melanin. Skin cancers are tumors that grow out of the skin [15]. They are triggered by the production of irregular cells and may infiltrate to certain areas on the human body. Skin cancer is categorized into three types: Basal-Cell Cancer (BCC), Squamous-Cell Cancer (SCC), and melanoma. BCC and SCC are mild skin cancers. The most dangerous one is melanoma. Symptoms include a mole that has evolved in scale, form, color, uneven borders, more than one shade, becomes itchy, or bleeds [16].

Visual imaging for skin cancer diagnosis by medical professionals may not guarantee 100% recognition of malignant or benign cancers [17]. Therefore, automatic classification systems for the detection and classification of skin cancers are urgently needed, which can be accurate and successful [18]. Among the existing clinical methods for melanoma detection, the very first dermoscopic technique for the treatment of melanoma was pattern analysis of these images is very challenging having some troublesome factors like light reflections from the skin surface, variations in color illumination, different shapes, and sizes of the lesions class discrepancy of melanoma and related noise interference [19]. To extract more distinguishable pathological features, multi-CNN collaborative training dermoscopy image lesion recognition model, improves the robustness of lesion identification and verified the effectiveness of the proposed method on related data sets [20].

The performance of the deep learning-based system on skin lesion detection has been evaluated against dermatologists and the conventional machine learning techniques in the recent past [21]. The possibility and the advantages of using artificial intelligence are done for skin cancer classification against dermatologists [22]. They established that Convolutional Neural Network (CNN) outperforms humans in the task of skin cancer classification. The classification of skin lesions using a single CNN was trained end-to-end using only images' pixels and disease labels of skin lesions as inputs [23]. CNN possess the ability to classify images of skin cancer on par with dermatologists and can as well enable life-saving and quick diagnoses, through the installation of apps on mobile devices most especially outside the hospital. The performance of deep learning-based techniques with traditional machine learning techniques, such as, Support Vector Machine (SVM) in the detection and classification of skin lesions are performed [24]. They utilized three techniques: SVM, VGGNet,and Inception-ResNet-v2, for the classification of seven categories of skin diseases. Although existing deep learning techniques has the ability to learn highly discriminative features, their performance is still limited due to the following reasons: (1) Training deep learning methods with limited labeled data can lead to over-fitting and poor generalization. (2) Most deep learning methods require higher memory and computational resources with heavy reliant on millions of parameters tuning to perform efficiently. (3) The deep learning approach also needs to be able to process multi-scale and multi-resolution features since the skin lesion images are always acquired with different devices with varying imaging resolution. (4) Automated detection of the skin lesion is also challenging due to the heterogeneous visual attributes of skin lesions images and fine-grained contrast in the appearance of skin lesions [25]. This study proposes a new deep learning framework for automated detection and classification of skin lesion images.

**Related works**

In 2020, Wei *et al.* [1] have proposed common feature extraction modules of lesion classification network and a feature discrimination network. Firstly, two sets of training samples (positive and negative sample pairs) is input into the feature extraction module (Lightweight CNN) of the recognition model. Then, two sets of feature vectors output from the feature extraction module are used to train the two classification networks and feature discrimination networks of the recognition model at the same time, and the model fusion strategy is applied to further improve the performance of the model, it can extract more discriminative lesion features and improve the recognition performance of the model in a small amount of model parameters; based on the feature extraction module of the proposed recognition model, U-Net architecture, and migration training strategy, we build a lightweight semantic segmentation model of lesion area of dermoscopy image, which can achieve high precision lesion area segmentation end-to-end without complicated image preprocessing operation.

In 2021, Pacheco and Krohling [2] have developed a Metadata Processing Block (MetaBlock), a novel algorithm that uses metadata to support data classification by enhancing the most relevant features extracted from the images throughout the classification pipeline. The other two combination approaches: the MetaNet and one based on features concatenation. Results obtained for two different skin lesion datasets show that our method improves classification for all tested models and performs better.

In 2020, Adegun and Viriri [3] have proposed two stages: the first stage leverages on an encoder-decoder Fully Convolutional Network (FCN) to learn the complex and inhomogeneous skin lesion features with the encoder stage learning the coarse appearance and the decoder learning the lesion borders details. FCN was designed with the sub-networks connected through a series of skip pathways that incorporate long skip and short-cut connections unlike, the only long skip connections commonly used in the traditional FCN, for residual learning strategy and effective training. The network also integrates the Conditional Random Field (CRF) module which employs a linear combination of Gaussian kernels for its pairwise edge potentials for contour refinement and lesion boundaries localization. The second stage proposes a novel FCN-based DenseNet framework that was composed of dense blocks that are merged and connected via the concatenation strategy and transition layer.

In 2020, Paul and Kabir [4] have developed a preprocessing of dermoscopic images to remove hairs with the Maximum Gradient Intensity algorithm and also enhancement of the images was done. Segmentation based on Otsu Thresholding algorithm was applied to separate skin lesions from the images. Multiple features like ABCD, GLCM, and LBP are then calculated from the segmented images which will be used to train a neural network. The network was successful to attain an accuracy of 97.7% on the combined dataset of ISIC archive the PH2 dermoscopic image database. The proposed method was found to be more accurate than existing methods and encorporates much more feature information from the images.

In 2022, Bratchenko *et al.* [5] have proposed a most common malignancy in whites accounting for about one third of all cancers diagnosed per year. Portable Raman spectroscopy setups for skin cancer "optical biopsy" are utilized to detect tumors based on their spectral features caused by the comparative presence of different chemical components. However, low signal-to-noise ratio in such systems may prevent accurate tumors classification. Thus, there is a challenge to develop methods for efficient skin tumors classification.

In 2021, Ali *et al*. [6] have developed a Deep Convolutional Neural Network (DCNN) model based on deep learning approach for the accurate classification between benign and malignant skin lesions. In preprocessing, apply filter or kernel to remove noise and artifacts; secondly, normalize the input images and extract features that help for accurate classification; and finally, data augmentation increases the number of images that improves the accuracy of classification rate. To evaluate the performance of our proposed, DCNN model is compared with some transfer learning models such as AlexNet, ResNet, VGG-16, DenseNet, MobileNet, etc. The model was evaluated on the HAM10000 dataset. The final outcomes of DCNN model define it as more reliable and robust when compared with existing transfer learning models.

In 2020, Adegun and Viriri[7] have proposed deep learning-based method that overcomes these limitations for automatic melanoma lesion detection and segmentation. An enhanced encoder-decoder network with encoder and decoder sub-networks connected through a series of skip pathways which brings the semantic level of the encoder feature maps closer to that of the decoder feature maps was proposed for efficient learning and feature extraction. The system employs multi-stage and multi-scale approach and utilizes softmax classifier for pixel-wise classification of melanoma lesions. A new method called Lesion-classifier that performs the classification of skin lesions into melanoma and non-melanoma based on results derived from pixel-wise classification. Our experiments on two well-established public benchmark skin lesion datasets, demonstrate that our method was more effective than some state-of-the-art methods.

In 2021, Toğaçar *et al.* [8] have developed a model that relies upon the auto encoder, spiking, and convolutional neural networks is proposed to ensure a useful decision support tool in this study. The original dataset and structured dataset were trained and classified by the MobileNetV2 model that consists of residual blocks, and the spiking networks. As a result, it was seen that the auto encoder model and spiking networks contributed to enhancing the performance of the MobileNetV2 model.

**Problem Definition**

Skin cancer includes in many types that can be classified as severe or superficial. Consequently, treatment of skin cancer depends on the degree of severity an affected individual. Some of the major challenges acquired in the skin cancer detection process are redesigning the research pipeline, developing the preclinical models, understanding the cancer growth level, providing early treatment, handle complex cancers precise manner and so, its need to design an alternative model for increasing the accuracy rate and it helps the physicians to give early or second opinion. Many techniques have been implemented for skin cancer detection and classifications are depicted in the Table 1. Lightweight CNN [1] provides fine-grained classification in feature discrimination, it can’t able to adjust the hyper parameters, also it is unstable during training period. MetaBlock [2] achieves higher performance by taking patient’s demograph so, it provides less performance in the melanoma classification. FCN-based DenseNet [3] employs hyper-parameters optimization techniques to reduce network complexity and improve computing efficiency, sometimes; it undergoes over-fitting and poor generalization problems and needs more computing resources. ANN Classifier [4] used in the target function and the output may vary based on discrete-value, real- value or vector of discrete-valued attributes and minimize the size of the computational resources so it needs higher level training to operate and it allows only trained models to extract the features from the images. CNN [5] is not highly sensitive by using optical biopsy to detect tumours based on their spectral features so; it didn’t encode the position of the object in the processing time. DCNN [6] provides high robustness and more reliability on skin cancer detection at the same time it doesn’t support large dataset with more labeled skin lesions. Deep Convolutional Architecture [7] has high computational speed during the training phase some time it doesn’t support real time system for medical diagnosis task in diagnosing melanoma cancer. MobileNetV2 [8] is highly efficient in extracting 1000 number of features in the Logits layer so, it doesn’t provide efficient features alone with input data and also needs to change in parameter value for different types of datasets. So, it is necessary for an alternative and advanced deep learning model for the detection and classification of skin cancer.

**Table 1:** Features and challenges of existing skin cancer detection and classification models

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| --- | --- | --- | --- |
| **Author [citation]** | **Methodology** | **Features** | **Challenges** |
| Wei *et al.* [1] | Lightweight CNN | * It provides fine-grained classification in feature discrimination. | * It is unable to adjust the hyper parameters. * It is unstable during training. |
| Pacheco and krohling [2] | MetaBlock | * It achieves higher performance by taking patient’s demograph. | * It provides less performance in the melanoma classification. |
| Adegun and Viriri [3] | FCN-based DenseNet | * It employs hyper-parameters optimization techniques to reduce network complexity and improve computing efficiency. | * It undergoes over-fitting and poor generalization problems. * It needs more computing resources. |
| Paul abd Kabir [4] | ANN Classifier | * It is used in the target function and the output may vary based on discrete-value, real- value or vector of discrete-valued attributes. | * It needs higher level of training to operate. * It allows only trained models to extract the features from the images. |
| Bratchenko *et al.* [5] | CNN | * It is not highly sensitive by using optical biopsy to detect tumours based on their spectral features. | * It didn’t encode the position of the object in the processing time. |
| Ali *et al* [6] | DCNN | * It provides high robustness and more reliability on skin cancer detection. | * It doesn’t support large dataset with more labeled skin lesions. |
| Adegun and Viriri [7] | Deep Convolutional Architecture | * It has high computational speed during the training phase. * It minimizes the size of the computational resources. | * It doesn’t support real time system for medical diagnosis task in diagnosing melanoma cancer. |
| Toğaçar *et al.* [8] | MobileNetV2 | * It is highly efficient in extracting 1000 number of features in the Logits layer. | * It doesn’t provide efficient features alone with input data and also needs to change in parameter value for different types of datasets. |

**Research Methodology**

The complex detection background and lesion features make the automatic detection of dermoscopy image lesions face many challenges. The previous solutions mainly focus on using larger and more complex models to improve the accuracy of detection, there is a lack of research on significant intra-class differences and inter-class similarity of lesion features. At the same time, the larger model size also brings challenges to further algorithm application. Hence, a new trio-phased skin detection and classification model is designed with the ensemble learning approach. The proposed model will include (a) Image collection, (b) Pre-processing, (c) Classification Model 1, (d) Classification Model 2, (e) Classification model 3 and (f) Final Classification Phase. Initially, the images related to skin diseases will be collected from the standard benchmark datasets. The gathered images will be used for pre-processing phase with the filtering and CLAHE approach. The pre-processed images will be given into the classification model 1, where the segmentation will be performed with the Deeplabv3 and the segmented images will be considered for the ensemble deep learning approach by integrating the DenseNet, Mobilenet, VGG16, Resnet and Inception network. Then, the high ranking-based classification will takes place between these ensemble classifiers to get first highest rank. In the classification model 2, the pre-processed image will get segmented with Deeplabv3 and extracts the features like region props, GLCM and GLRM from the segmented images. These extracted features will be given into same ensemble classifiers and ranking between the classifiers will perform to acquire the second highest rank. In the classification model 3, the Deeplabv3-based segmentation will involve and then, the pattern extraction will be performed with LGP and LBP patterns. These obtained patterns will be incorporated into ensemble classifiers for obtaining the third highest rank. Finally, the three highest ranks from three classification models will be considered for getting the most accurate skin disease detection outcomes. Here, the parameter optimization takes place in the ensemble classifier at three models using the enhanced optimization technique of Red deer algorithm (RDA) [26]. The experimental results will be carried out for establishing the effectiveness of the proposed skin detection framework by comparing with the advanced techniques. The proposed architecture will be shown in Figure 1.

Image collection

Pre-processing phase

Highest rank 1

Highest rank 2

Highest rank 3

Final classification based on high ranking

Enhanced RDA-based ensemble classifiers

**Figure 1**: Architectural view of proposed skin disease classification and detection model

**Expected Outcome**

The proposed model will be compared over the conventional models with different quantitative measures. Here, Type I measures are positive measures like Accuracy, Sensitivity, Specificity, Precision, Negative Predictive Value (NPV), F1Score and Mathews correlation coefficient (MCC), and Type II measures are negative measures like False positive rate (FPR), False negative rate (FNR), and False Discovery Rate (FDR).

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