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Deep learning for skin melanoma classification using dermoscopic images in different color spaces

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ABSTRACT

Skin cancer begins in the skin cells. The damage to the skin cells can cause genetic mutations that lead to uncontrolled growth and the formation of tumors. It is estimated that millions of people are diagnosed with skin cancer of different kinds each year. The earlier a skin cancer is diagnosed, the better the patient's prognosis and the lower their chance of complications. In this work, an efficient deep learning classification (EDLCS) to classify dermoscopic images is developed. The importance of color in the diagnosis of skin melanoma has caused color analysis to attract considerable attention from researchers of image-based skin melanoma analysis. Three different color spaces such as red-green-blue (RGB), hue-saturation-lightness (HIS) and LAB are investigated in this study. The obtained dermoscopic images are in RGB color space. The RGB dermoscopic images are first converted into HSV and LAB spaces to investigate the HSV and LAB color spaces for melanoma classification. Then, the color space converted image is fed to the proposed EDLCS to evaluate their performances. Results show that the proposed EDLCS provides 99.58% accuracy while using the LAB color model to classify preprocessed images while other models provide 99.17%.

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1. INTRODUCTION

Skin cancer occurs when there is an abnormal proliferation of skin cells, which may be produced by exposure to sun's ultraviolet (UV) light and or from artificial sources. The tanning beds and some types of lasers are examples of artificial sources of UV radiation. The three primary forms of skin cancer are as follows:

a. Basal cell carcinoma (BCC): BCC usually manifests itself on regions of the skin, such as the face and the neck that are often exposed to the sun. In most cases, it takes the form of a tiny, elevated hump that may have a waxy or pearlescent look.
b. Squamous cell carcinoma (SCC): This kind of skin cancer is also often seen on portions of the skin that are exposed to the sun. It is also possible on other parts of the body as well. It manifests itself most often as a raised lump that resembles a wart or a scaly red patch.

c. Melanoma: This is the most serious skin cancer's type. It can extend to other areas of the body in its untimely stages if not treated properly. It typically seems as a dark, unevenly determined mole or spot on the skin. An estimated 106,110 new cases of melanoma and 4.3 million new non-melanoma instances occur in the United States every year [1]. Here are some additional skin cancer statistics: i) Over their lifetime, one out of every five Americans will be diagnosed with skin cancer; ii) Melanoma is the 5^{th} frequent cancer to occur in males and the 7^{th} common type of cancer to occur in women; iii) In the year 2021, it is anticipated that melanoma would claim the lives of around 7,180 persons; iv) The five-year survival percentage for persons with melanoma that has not gone beyond the skin is 99%, provided that the cancer has not progressed; v) Just 27% of persons with melanoma that has spread to other regions of the body will be alive after five years; vi) If a person has had more than five sunburns in their lifetime, their chance of acquiring melanoma is increased by a factor of two; and vii) Tanning bed usage before the age of 35 is associated with a 59% increased risk of acquiring melanoma in those who have already had the disease.

These statistics highlight the importance of protecting your skin from the sun's harmful rays and usually verifying your skin for any exchanges or abnormalities. Early detection and treatment can greatly improve outcomes for people with skin cancer. In India, skin cancer is not as common compared to other parts of the world, particularly in regions with lighter-skinned populations that are more susceptible to UV radiation damage. However, skin cancer is still a concern in India due to the high levels of UV radiation exposure in many regions, particularly in areas closer to the equator.

Skin cancer accounts for 1% to 2% of all cancers in India [2]. The incidence of skin cancer is higher in northern India, where UV radiation exposure is higher, compared to southern India. The types of skin cancer Occurs in India are BCC and SCC, which are primarily caused by sun exposure. Melanoma is relatively rare in India. Risk factors for skin cancer in India include spending prolonged periods of time in the sun, having fair skin, a family history, and a history of sunburns. Protecting one's skin from the harmful effects of UV from the sun is the most effective strategy to stave against skin cancer by wearing protective clothing, using sunscreen with at least SPF 30, and avoiding prolonged exposure to the sun during peak hours. It is also important to perform regular skin self-examinations and to have any unusual or changing moles or spots on the skin evaluated by a doctor.

2. RELATED WORKS

There have been several related works in the field of skin cancer categorization utilizing deep learning (DL) models. A DL model for skin cancer classification is described in [3]. It has 7 convolution layers and 3 neural layers for the purpose of classifying dermoscopic images. An efficient method is described in [4] for the early identification of skin cancer. DL architectures such as Inception-v3 and ResNet-101 are being used for the classification challenge. A skin cancer classification approach is demonstrated in [5]. The deep convolution neural network (DCNN), VGG16, and VGG19 models are trained and assessed for skin cancer diagnosis. An improved image classification model is built in [6] to assist dermatologists in the process of making diagnoses. This model is intended to serve as a preliminary check to avoid a more expensive biopsy. During the classification process, transfer learning is employed by combining it with data augmentation and class-weighted loss approaches.

A method that makes effective use of DL to identify skin cancer is suggested in [7]. After making adjustments to the pre-trained MobileNet convolution neural network (CNN), classification of dermoscopic images is achieved. This approach of transfer learning has shown outstanding accuracy over a broad spectrum. The skin lesions are classified in [8] using three cutting-edge DL pre-trained models. These models were ResNet, Xception, and DenseNet. A prescreening approach to diagnose cancer sooner in rural locations is described in [9]. A prototype of a gadget capable of segmenting the affected region of the skin into seven primary categories, as well as classifying the skin abnormality itself is provided. A Raspberry Pi 3B+, a magnifying camera attachment, a CNN that powers skin cancer recognition. Skin cancer boundaries are segmented using another model, and an interactive touchscreen user interface is all included in the prototype. The challenge of merging images and metadata characteristics to the classification of skin cancer is described in [10]. During the whole process of data classification, metadata processing block process is suggested. This algorithm makes use of metadata to help data classification along with the important characteristics derived from images. An ensemble of deep learners capable of detecting skin cancer has been constructed in [11] by combining the learners of the VGG, CapsNet, and ResNet models. Two different approaches for cross-domain skin cancer identification is investigated in [12]. A two-step progressive transfer learning approach is employed through the use of two different skin disease datasets that helps fine tuning the network. At first, a deep CNN classifier is pre-trained on ImageNet. Then, adversarial learning is designed to conduct an invariant attribute translation to provide good results.

A strategy is offered in [13] to fuse the characteristics of DL with the characteristic of traditional image processing. A hypothesis which has distinct error profiles is developed and they are complementary to one another. The traditional image processing arm consists of a clinical module and three image processing modules. The image processing modules are able to identify lesion characteristics that are analogous to clinical dermoscopy data, such as an abnormal pigment network, color distribution, and blood vessel distribution. A fully automated DL ensembles are presented in [14] for skin cancer classification. The ensemble techniques using Mask R-CNN and DeeplabV3+ approaches are developed.

A deep supervised multi-scale network (DSM-Network) is described in [15]. To handle different sizes of skin lesions, a multi-scale connection block is planned and aggregates information from shallow and deep layers. In addition, a conditional random field model uses post-processing to refine the skin contour. A lightweight model for the detection of skin cancer with feature discrimination is suggested in [16]. It is based on the notion of fine-grained categorization and has two feature extraction modules that are shared across them: feature discrimination and a lesion classification network. A hybrid data mining strategy is suggested in [17]. It integrates k-nearest neighbor (KNN) and support vector machine (SVM) to assemble up an accurate preparation for breast cancerous development estimate. The prediction of Alzheimer's disease has received a 20 percent enhancement in characterization accuracy. The scope of this model is applied to hybrid artificial intelligence (AI) calculations that organize SVM with CNN to expect Alzheimer's sickness and make a helpful model [18]. The radio frequency (RF) module builds wireless data transfer and transmission between the wearable devices. The sensor data and alerts announcement rapidly send to the cloud [19].

3. METHODS AND MATERIALS

The proposed efficient deep learning classification (EDLCS) is designed to classify the dermoscopic images for skin cancer diagnosis. An image classification system is a type of AI system that is designed to automatically classify images based on their content. Image classification systems use DL algorithms, such as CNNs, to analyze the features and patterns within an image and classify it into one or more predefined categories. The process of creating an image classification system typically involves training the system with a labeled image. During the training process, the system learns to identify the unique features and patterns within each category of images. Once the system is trained, it can then be used to test new images into the predefined categories. The working flow of the proposed EDLCS for skin melanoma classification using dermoscopic images in different color spaces is shown in Figure 1.

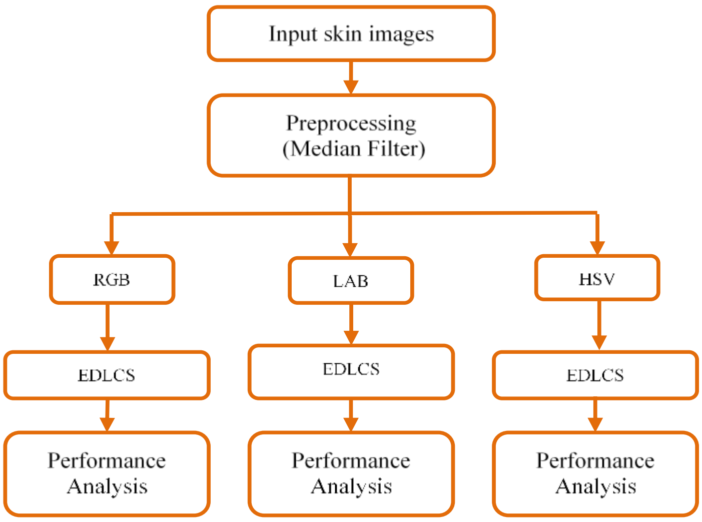


Figure 1. Skin melanoma classification process

3.1. Preprocessing

Image preprocessing is a series of operations performed on an image before it is analyzed or used for further processing. In image analysis and computer vision tasks, preprocessing is an important step, as it can improve the accuracy and reliability of the analysis by removing noise, enhancing contrast, and reducing the impact of artifacts in the image. Some common image preprocessing techniques include image resizing, image cropping, image filtering, image normalization and thresholding. In this work, median filtering [20] is employed for noise removal and image resizing is performed before classification. Filtering an image involves applying a mathematical operation to the pixels in the image to improve or eliminate definite features. Some common filters include Gaussian filters, median filters, and edge detection filters. Median filter is defined in (1).

$$MF_{ij} = median\{I_{i+k,j+l}: k,l = -s,\dots.s\} for i,j = (s+1),\dots..(n-s) \quad (1)$$

Here is the filter size. Figure 2 shows the preprocessing results of the EDLCS system. Figure 2(a) illustrates the input dermoscopic images and Figure 2(b) displays the median filtered dermoscopic images using a window of size (2s+1, 2s+1) filter.

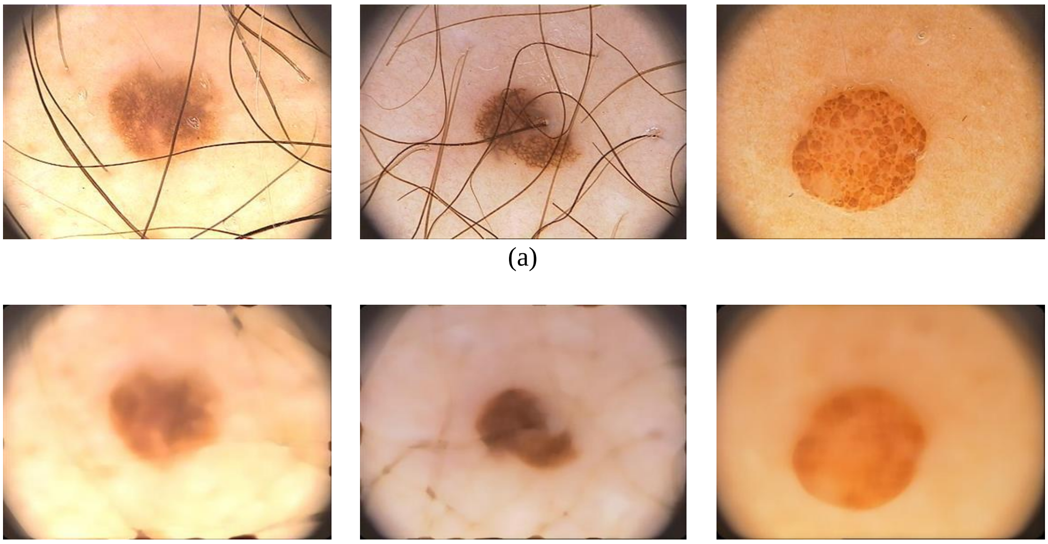


Figure 2. Preprocessing results of the EDLCS system is (a) input dermoscopic image and (b) median filtered image

3.2. Color domain

A color space describes how colors can be represented using numbers. Color spaces are used to specify and communicate color information in various applications, including digital imaging, printing, and video production. The option of color space calculates on the detailed application and the type of color information that needs to be represented. There are several types of color spaces, but the most common are red, green, blue (RGB), LAB and hue, saturation, value (HSV).

- Red, green, blue (RGB) color space: Each color channel in the RGB colour space such as red, green, and blue light ranging from 0 to 255. By aggregating various levels of red, green, and blue, a wide range of colors can be represented [21].
- LAB color space: In the LAB color space, the L parameter represents lightness and ranges from 0 (black) to 100 (white). The *a* parameter represents the degree of redness or greenness, with positive values showing red and negative values showing green. The *b* parameter represents the degree of blueness or yellowness, with positive values showing yellow with negative values showing blue. The *a* and *b* parameters range from -128 to 127. More information can be found in [22].
- Hue, saturation, lightness/value (HSL/HSV) color space: It plays colors as a arrangement of hue, saturation, and lightness or value. Lightness or value represents the brightness of the color, saturation indicates the purity otherwise the color intensity, and hue indicates the color itself. More information can be found in [23].

3.3. Deep learning architecture

DL has been highly successful in recent years [24], [25] and many of the most significant breakthroughs in artificial intelligence have been made possible by advances in DL algorithms and techniques. DL has a great deal of potential to transform various aspects of healthcare that includes improved diagnostics, optimized drug discovery process, and personalized treatment. X-rays, magnetic resonance imaging, and pathology slides are all examples of medical images, which are successfully analyzed by DL models. This helps in the early identification and diagnosis of diseases such as cancer, Alzheimer's disease, and diabetic retinopathy. Figure 3 shows the proposed structure of the EDLCS for skin cancer diagnosis.

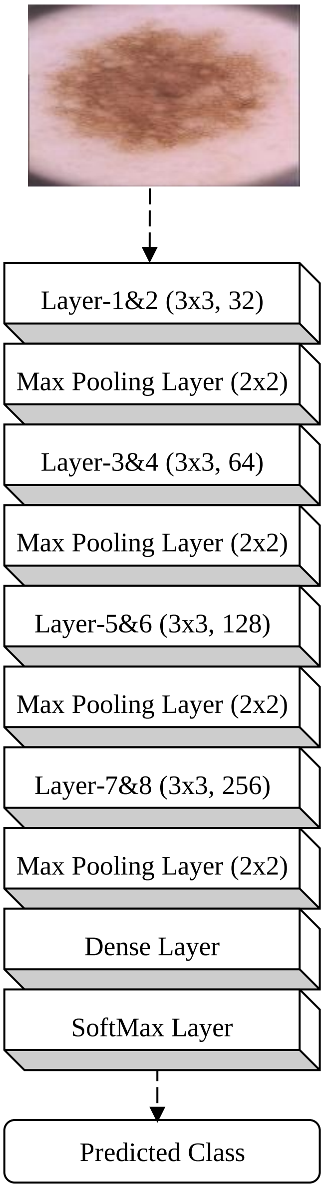


Figure 3. Proposed EDLCS design

3.3.1. Convolution layer

It is a primary building block in CNNs utilized for image processing and computer vision tasks. To derive feature maps from an input image, a convolutional layer employs a set of learnable filters on the input, and then convolves the two. The input image is passed through each filter, which is a tiny matrix of weights that performs a dot product operation at each spatial point. This operation will result in the production of a feature map as its output. This feature map will reflect the activation of that filter at each position in the input. The main advantages of convolutional layers are their ability to extract local features and their parameter sharing property. By learning shared filters, a convolutional layer can capture spatial patterns across the entire input image, making it well-suited for tasks like object detection and recognition. Convolutional layers typically include several hyper-parameters, such as the number of filters, filter's size, the stride of the convolution operation, and the padding applied to the input image. These hyper-parameters can be tuned to optimize the functioning of the model on a specific task. In this mechanism, the convolution layers are arranged in an efficient manner to achieve more accuracy than other architectures.

3.3.2. Max pooling layer

It reduces the input's spatial dimensions by taking the maximum value of a fixed-size window (usually 2×2 or 3×3) and sliding it over the input feature map. During max pooling, the input is divided into sub-regions, and each sub-region's maximum value is taken to produce a smaller output feature map. This operation helps reducing the spatial dimensions, while retaining the most significant information present in the input. Max pooling layers have several advantages, including the ability to extract dominant features from the input feature map while reducing the effect of local variations and noise. They also help in reducing the computational cost and the number of parameters required in the network, by down-sampling the feature maps. Max pooling layers in combination with convolutional layers can be used to extract hierarchical representations of the input image. By alternating between convolutional layers and max pooling layers, CNNs can learn to detect features of increasing complexity in the input image.

3.3.3. Dense layer

A dense layer is a type of neural network. Each neuron in the feedforward network is associated to each neuron in the previous layer. Each neuron computes a weighted sum of the previous layer's inputs. Then, an activation function is employed to produce an output. Dense layers are commonly used for various tasks such as natural language processing (NLP), image classification and the prediction of time series. They are particularly useful for tasks that require learning complex and nonlinear relationships between inputs and outputs. The complexity of model depends on the number of neurons and its ability to represent the underlying function. The activation function helps introduce nonlinearity in the model and is typically a rectified linear unit (ReLU) or sigmoid. Dense layers can be used as neural network's output layer, where the number of neurons in the layer represents the number of categories in a categorization issue or the number of outputs.

3.3.4. SoftMax layer

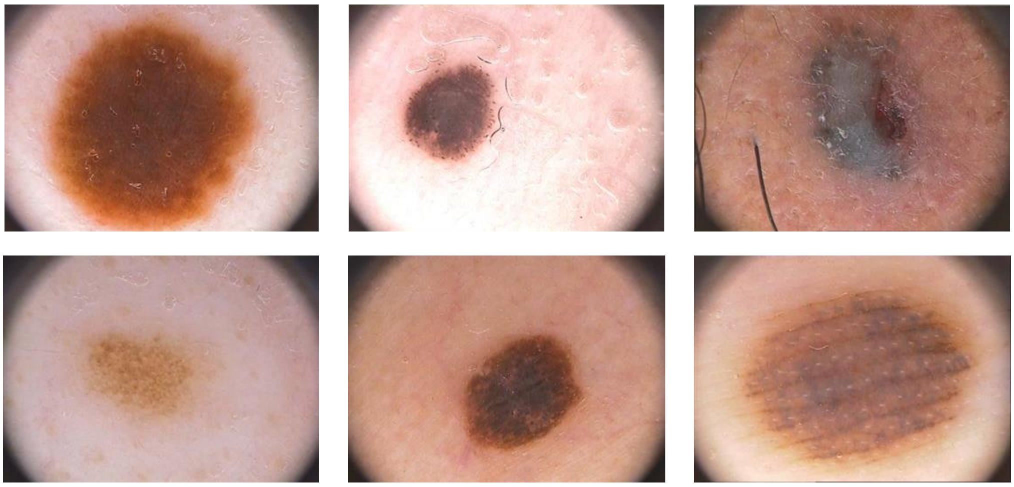
A SoftMax layer is a commonly used layer in neural networks, particularly in the context of classification problems. It is typically the last layer and is used to transform the outputs of the previous layer into a probability distribution over the different classes. The SoftMax function returns a vector of the same size as the input vector (real numbers), where each element is a non-negative number between 0 and 1, and the sum is 1. To do this, exponentiate every element in the input vector, and then divide the output vector's elements by the total of all the exponentiated values to normalize it. It is common practice to combine the SoftMax layer with a loss function such cross entropy loss. The difference between the anticipated and actual probability distributions—that is, the one-hot encoding of the true class label—is calculated using the cross entropy loss. Overall, the SoftMax layer plays a crucial role in converting the outputs of a neural network into a probability distribution over the classes, which can then be used to make predictions.

4. RESULT AND DISCUSSION

The PH2 database [26], [27] is a publicly available database of dermoscopic images of pigmented skin lesions, which is designed to aid in the diagnosis of melanoma. The PH2 database was created by a team of researchers from the University of Porto in Portugal and contains a total of 200 images of skin lesions. This database is notable for its high-quality dermoscopic images, which are captured using a high-resolution camera and a dermatoscope. The images are captured under standardized conditions, with consistent lighting and camera settings, to ensure that the images are of high quality and comparable to each other.

Each image in the database is accompanied by a set of ground truth annotations, including the diagnosis, the type of lesion, and the location of the lesion on the body [28], [29]. The PH2 database has been used in several research studies to develop and evaluate the developed algorithms. Figure 4 shows the sample dermoscopic images in the database. Figure 4(a) shows the normal images from the PH^2 database, and the atypical nevus and melanoma images are shown in Figures 4(b) and 4(c) correspondingly.

Hyper-parameter tuning is an important part of the machine learning workflow, as the choice of hyper-parameters can greatly affect the performance of the model. They are set prior to the training process, and also govern the behavior of the training process of a machine learning model. These parameters cannot be learned from the data and must be set manually or using some automated search algorithm Table 1 shows the hyper-parameters used in this work. The performance of the proposed EDLCS design is analyzed using three measurements: for example, accuracy, sensitivity and specificity. Table 2 shows the obtained performance metrics for different color models.



(a) (b) (c)

Figure 4. Database images (a) normal, (b) Atypical Nevus, and (c) Malignant or Melanoma

Table 1. Hyper parameters used in the proposed EDLCS design

Hyper parameters	Values
Convolution layer filter size	3×3
Number of convolution filters	32, 64, 128 and 256
Stride in convolution	1
Activation function (input)	ReLU
Max pooling layer filter size	2×2
Stride in max pooling layer	2
Activation function (output)	softmax
Loss function	Cross entropy loss
Optimization	Mini-batch gradient descent algorithm

Table 2. Performance of the proposed EDLCS design under different color models

Condition of input dermoscopic images	RGB	LAB	HSV
	Accuracy (%)		
No preprocessing	96.67	98.54	97.29
Preprocessing by median filter	99.17	99.58	99.17
	Sensitivity (%)		
No preprocessing	97.57	98.96	98.26
Preprocessing by median filter	99.31	99.65	99.31
	Specificity (%)		
No preprocessing	95.31	97.92	95.83
Preprocessing by median filter	98.96	99.48	98.96

It is observed from Table 2 that the LAB color model provides better results than other two-color models used in this study for the classification of dermoscopic images. This is due to the fact that the LAB color space defines color differences, building it functional for color analysis. It is a three-dimensional color space which indicates the colors established on the three parameters of lightness, a (red-green), and b (blue-yellow).

5. CONCLUSION

Skin cancer develops usually by exposure to UV radiation from the sun or lamps or tanning beds. The uncontrolled growth of damaged skin cells leads to the formation of skin cancer. The early detection helps to reduce the risk of complications and better treatment. In this paper, EDLCS is developed for skin cancer diagnosis. It uses three color space models such as, RGB, LAB and HSV are employed, and their individual color components are fed to the proposed EDLCS. Before fed to the system, the input images are filtered to remove the noises and hairs by median filter and then they are represented by different color models. The final prediction results from the EDLCS is either normal or abnormal Results show that the proposed EDCLS provides promising results for all color models and the LAB color model provides better results than other models with an overall accuracy of 99.58%.

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