JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Leveraging Machine Learning for Early Detection of Skin Cancer Through Image Processing

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ABSTRACT: Skin cancer is one of the most common forms of cancer globally, with melanoma being the deadliest type. Early detection plays a crucial role in improving treatment outcomes and survival rates. Traditional methods of diagnosis, which rely on visual inspection by dermatologists, can be subjective and prone to errors. This paper proposes a novel approach to skin cancer detection by integrating machine learning algorithms with advanced image processing techniques. By analyzing dermatological images of skin lesions, image processing methods such as segmentation, feature extraction, and texture analysis are used to enhance and classify the images for accurate diagnosis. Subsequently, machine learning models, including Convolutional Neural Networks (CNNs), are employed to classify skin lesions as malignant or benign based on extracted features. The system's performance is evaluated using standard datasets, achieving promising results in terms of accuracy, sensitivity, and specificity. This research demonstrates the potential of automated image analysis in aiding early skin cancer detection, offering a reliable, efficient, and scalable solution for clinical applications. The findings highlight the significant role of artificial intelligence in enhancing the diagnostic process and supporting healthcare professionals in making informed decisions**.**

Keywords*:* melanoma, image preprocessing, hair removal noise reduction, *CNN*, *ResNet*, *DenseNet*

I. INTRODUCTION

Healthcare has changed due to recent technological advances, especially machine learning and Artificial intelligence (AI). Machine learning, in particular, has shown potential in processing functional images, opening new avenues for diagnostic applications.

The project aims to leverage the power of machine learning and imaging to detect skin cancer. By training a machine learning model on skin cancer treatment data, we sought to develop a system that can identify patterns that indicate skin cancer. In addition to training models, we plan to present the solutions through a user-friendly website. The platform will allow doctors, especially dermatologists, to upload skin photos for analysis. This not only simplifies the diagnostic process but also facilitates remote communication and commonly used diagnostic tools. The project combines machine learning and imaging to solve the problem of skin cancer diagnosis to provide effective and efficient solutions.

[1] discussed the preprocessing techniques for skin cancer detection play a crucial role in improving image quality and reducing errors. Researchers focus on image enhancement and restoration. Techniques include color space transformation, contrast enhancement,and denoising. Additionally, methods to remove thick hairs are essential. These preprocessing steps pave the way for accurate skin cancer diagnosis.

[2] discussed preprocessing techniques for medical imagery, focusing on X-ray, mammogram, and fundus images1. Denoising methods include mean, median, and adaptive filters. Enhancement techniques involve histogram equalization, illumination equalization, and contrast-limited adaptive histogram equalization (CLAHE).

[3] presents a study on plant leaf disease classification. It employs machine learning and image preprocessing techniques. The author reached to an accuracy of 98% using CNN.

[4] discusses melanoma skin cancer detection techniques. They compared traditional image processing with current technologies. Current technologies include CNNs, ANN, and SVM. Accuracy ranges from 81.61% to 94.0%. The goal is early detection to improve patient treatment.

[5] investigates skin cancer classification. They employs various techniques, including deep learning, support vector machines (SVM), and random forests. The prediction results of such a configuration are 81.46% AUC, 74.75% accuracy, 90.09% sensitivity, and 72.84% specificity.

[6] proposed three methods for binary classification of skin cancer lesions using smartphone images. The methods employed different CNN architectures: Alex-net, Mobilenet-V2, and Resnet-50. These models were divided into two groups: one with transfer learning on original data and the other with transfer learning on augmented data. The best performance was achieved by Alex-net with transfer learning and data augmentation, achieving 99% accuracy, 96.364% sensitivity, 99.792% specificity, 99.167% precision, and 97.661% F1-score.

[7] present a melanoma detection method using anisotropic

diffusion filtering, fast bounding box segmentation, and feature extraction via Hybrid Feature Extractor (HFE) and VGG19-based CNN. The HFE fuses Histogram-Oriented Gradient, Local Binary Pattern, and Speed Up Robust Feature into one vector1. This hybrid technique outperforms previous methods, achieving an impressive accuracy of 99.85%.

[8] used data augmentation strategies in the initial stage to enhance the number of training samples. A Medical Vision Transformer (MVT) model is used in the second layer to divide input images into patches and supply them to the transformer. With an overall accuracy of 96.14%, the MVT outperforms state-of-the-art methods for classifying skin cancer.

[9] presented a novel approach for skin cancer classification and segmentation using image processing and machine learning. It employs preprocessing techniques like contrast stretching and OTSU thresholding for segmentation. Features including texture, shape, and color are extracted and reduced, with classifiers such as SVM, Quadratic Discriminant, and Random Forest achieving up to 93.89% accuracy on the ISIC-ISBI 2016 dataset.

Presented a method to detect skin cancer from dermoscopic images using multiple features and classifications. The paper uses machine learning algorithms such as SVM, KNN, and random forest for classification evaluation. Ÿ The authors used random forest distribution of the data used in the study and achieved 93.5% accuracy. Its accuracy is approximately 86% for GRLLM, 84% for discrete time, and 89% for GLCM features.

Utilized a modified deep neural network algorithm called YOLO (You Look Only Once) for melanoma detection. They an accuracy of 98.16%, sensitivity of 95.43%, specificity of 99.50%, precision of 99.95%, and AUC of 0.99.

Proposed two methods, one using convolutional neural networks (CNNs) and the other using support vector machines (SVMs). The CNN model achieved a 91% accuracy rate after 100 compute epochs, while the SVM classifier achieved an 86.6% classification accuracy.

II. Proposed Work

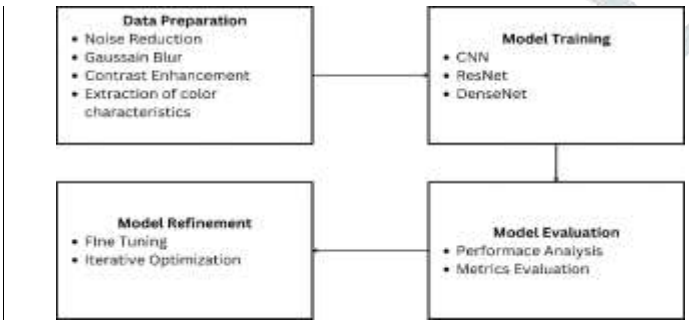

Fig. 1. Proposed Architecture

The project focuses on developing a robust skin cancer detection system using advanced image processing and machine learning techniques. The primary objective is to automate the identification of skin cancer, particularly melanoma, by leveraging computer vision. The systematic workflow involves preprocessing skin lesion images, applying novel techniques for segmentation, and extracting critical features for accurate classification. Transfer learning with pre-trained models like *CNN*, *ResNet*, Inception, EfficientNet, and *DenseNet* is employed to capitalize on their expertise in image recognition. Future directions involve real-world deployment considerations and ongoing enhancements based on emerging technologies and research findings. The dataset used is HAM10000 which contains a total of 10,000 images containing 7 different classes.

To enhance the understanding of color traits in the records, the RGB values of every color are extracted and stored in a brand-new report. This shade scheme's objective is to capture specific hues related to unique types of cancers. After this, a visible illustration of the color distribution of every cancer type was created, and hues of different cancer kinds. with the aid of analyzing these coloration distribution pix, in-depth expertise of the characteristics of color precise to each cancer type is obtained, imparting essential statistics for subsequent category studies. This approach now not only gives a deeper understanding of the coloration of records but also lays the inspiration for the improvement of extra effective classification models that could distinguish exclusive types of diseases, which includes most cancers, with the aid of color. between individual channel means and the overall grayscale mean.

Calculation of Mean Values:

- The mean values for each channel (Red, Blue, Green) have been calculated for every image in the dataset.
- A new data frame is created to store these mean values.

1. Normalization of Mean Values:

- The mean values for each channel are normalized by dividing them by the mean grayscale value of the corresponding image.
- This normalization ensures that the mean values are relative to the overall brightness of each image.

2. Resulting Dataset:

- The data frame now contains columns representing the mean values for Red, Blue, and Green channels and the normalized values.
- The dataset has additional information about the color characteristics of each image, considering the relationship between individual channel means and the overall grayscale mean.

Table 1 gives a detailed analysis of color value which is obtained from each of the 7 classes with their respective

Red, blue , green and gray mean values.

Fig. 2. Original image

Fig. 3. Enhanced image after pre-processing

Table I. Mean color value for each class

Mean Type / Classes	Red Mean	Green Mean	Blue Mean	Gray Mean
Benign keratosis	1.151009	0.950032	0.898958	154.950316
Melanocytic nevi	1.255341	0.889795	0.854864	160.030256
Dermatofibroma	1.173509	0.937380	0.889111	169.645912
Melanoma	1.160387	0.942820	0.896793	153.560745
Vascular Lesion	1.173204	0.953163	0.873633	169.843232
Basal Cell Carcinoma	1.143414	0.947624	0.908962	171.148270
Actinic Keratoses	1.187207	0.923102	0.889691	167.419745

III. MODEL TRAINING

i) Convolution Neural Network:

Convolution operation:

The convolution operation needs to apply a filter to the input image. It can be expressed mathematically as:

$$Si, \mathrm{j} = (IK), \mathrm{j} = \mathrm{Z}mZnIm, n \cdot Ki - m, \mathrm{j} - n \qquad (2)$$

where S is the output, l is the input image, K is the filter, and i and j are spatial coordinates.

Pooling work:

Pooling reduces the spatial dimension. For example, max pooling selects the maximum value in the pool and the mathematical expression is:

$$Oi, \mathrm{j} = maxm, n\, I.(i \cdot s + m, \mathrm{j} \cdot s + n) \qquad (3)$$

where O is output, I is input and s is step.

Softmax start:

The Softmax function converts the raw score into a result; this is defined for k groups as:

$$PY = k = (ezk)/(\mathrm{Z}jezj) \qquad (4)$$

$P_{Y=k}$ is the probability of the input that belongs to class k where z_k are the raw scores of the k categories.

CNN studied pores and skin cancer prognosis to discover ways to perceive styles and functions that indicate different pores and skin kinds. Mathematical processing in layers permits the version to output hierarchical representations,

making it an effective device for photograph-primarily based diagnostics. Convolutional Neural Networks (CNN) are used to classify the pores and skin of most cancer cells using the HAM10000 dataset. This version was trained with facts augmentation and carried out a training accuracy of 94%. but, throughout validation and checking out, the accuracy dropped to 76% and 75% respectively. This points to the potential for overfitting and shows that similar studies are needed, along with ongoing operational

ii) ResNet

In a multilayer neural network model, consider a subnetwork with a certain number (e.g. 2 or 3) of stacked layers. Denote the following operations performed by a network subnet as H(x); where x is the entry of the subnet. The concept of "residual learning" reparametrizes the subnet so that the parameter set represents the residual function

$$(x) = (x) - x \quad (5)$$

$$Y = (x) + x \quad (6)$$

The function F(x) is usually represented by matrix multiplication interspersed with boosting and normalization functions (such as batch normalization or layer normalization). This subnet is called the "left main". Deep residual networks are created by stacking a series of residual blocks.

The function "+x:" in "y = F(x) + x" is the remaining block and its output is processed by self-mapping and cross-linking ideas. In future studies, this connection is often referred to as the "residual connection.

iii) DenseNet

DenseNet is a Convolutional neural network (CNN) that uses dense connections between layers. Healing is done using a "feed-forward" nature where each layer takes as input all previous layers and passes its hierarchy of features to all subsequent layers. with dense blocks where each layer is connected directly to every other layer with the same map size, as opposed to the traditional stacking of layers which are connected to the previous and next layer. This promotes gradient flow, allowing aforementioned gradients to be back-propagated more directly through the network.

Mathematically speaking, if we represent the feature map of the Lth layer as H_L, the feature map of the (L + 1) layer will be calculated as follows:

$$X\{L+1\} = H\{L+1\}([X0, X1, \ldots, XL]) \quad (7)$$

Where $[X_0, X_1, \ldots, X_L]$ represents the union of feature maps of all previous layers, $H_{\{L+1\}}$ (It is the nonlinear transformation layer used by L+1).

This type of dense coupling allows efficient reuse and has been proven to improve the performance of CNNs on various image classifications. DenseNets achieves state-of-the-art results on many datasets, including CIFAR, SVHN, and ImageNet using fewer measurements than other high-performance CNN.

iv) ADAM classifier

In the case of the DenseNet model, its performance was likely supplemented by the Adam optimizer's ability to enhance accuracy. This lies in its efficient and adaptive nature, which computes individual learning rates for different parameters. This is based on the first moment estimates and the « exponentially weighted » infinity norm of the gradients first introduced in this paper. This approach can be particularly advantageous for training deep neural networks, of which DenseNet is an example.

There are a few reasons why this Adam optimizer can improve such deep learning systems. As it optimizes the learning rate for each parameter separately, it can accommodate different magnitudes of gradients across parameters. This adaptability is particularly useful for smoothing and accelerating convergence. That is, Adaptive Moment Estimation can smooth iterations in this way such that they're not dogged by the kinds of vanishing and exploding gradients that are hallmarks of training deep networks. Consequently, DenseNet which was trained with the Adam optimizer can explore the complex parameter space of the type involved here and zero in out quickly.

IV. RESULTS AND DISCUSSION

By applying all three models and evaluating each of them based on three phases that is training, validation and testing following numbers has been received.

Fig 4 shows the training vs validation accuracy of CNN, training accuracy started from 66% and went till 80% and validation accuracy started from 69% and increases till 78%. Fig 5 shows the training vs validation loss fro CNN where training loss and validation loss started from nearly 1 and went to decrease to 0.6 and 0.5 respectively.

Fig 6 shows the training vs validation accuracy of ResNet. Training accuracy started from 70% from first epoch and reached 94% by the 30th epoch while validation accuracy starting from 73% and alternatively increasing and decreasing between 80 to 85%. Fig 7 shows the training vs validation loss where training and and validation loss started from 8 and 9 respectively and training loss declined to 0.2 while validation loss declined to 0.6 by the 5th epoch and remained constant.

Fig 8 shows the training vs validation accuracy of DenseNet. Both training and validation accuracy started at nearly 75% then training accuracy went to reach 99% while validation accuracy reached 85% by the 8th epoch and remained constant. Fig 9 shows the training vs validation loss where training loss started from 0.75 and declined to almost 0.02 while validation loss started from 0.8 and declined to 0.4 by the 4th epoch and keeps on toggling between 0.64 to 0.4 from 5th epoch to 30th epoch.

Fig. 4. Training Accuracy v/s Validation Accuracy (per epochs) for CNN

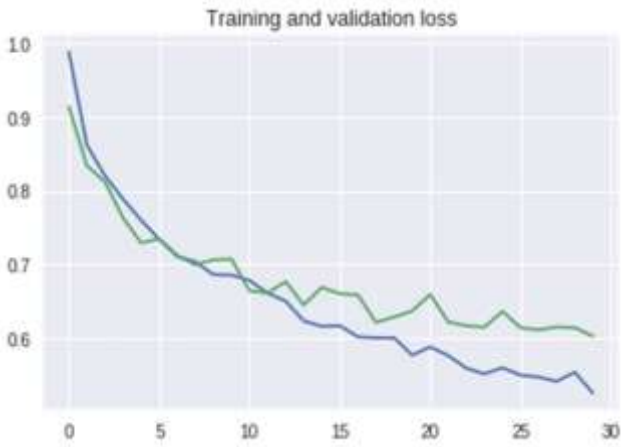

Fig. 5. Training Loss v/s Validation Loss (per Epochs) For CNN

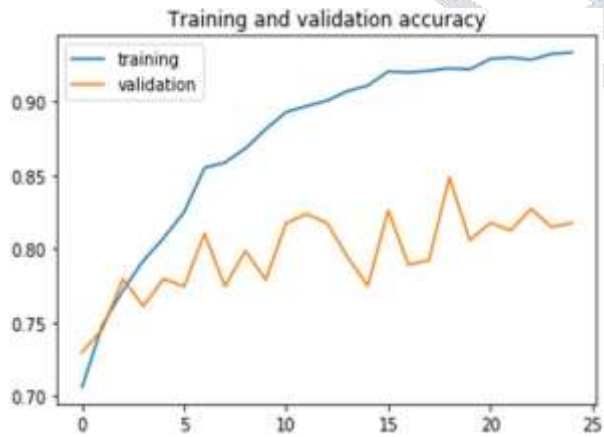

Fig. 6. Training Accuracy v/s Validation Accuracy (per epochs) for ResNet

Fig. 7. Training Loss v/s Validation Loss (per Epochs) For ResNet

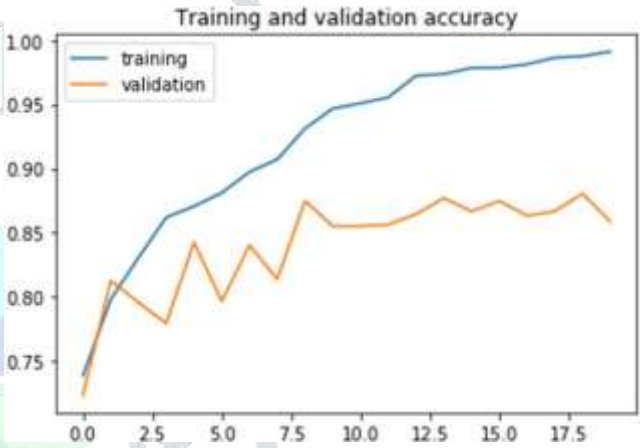

Fig. 8. Training Accuracy v/s Validation Accuracy (per Epochs) for DenseNet

Fig. 9. Training Loss v/s Validation Loss (per Epochs) For DenseNet

Table II. Quantitative Analysis

Measures / Algorithms	Epochs	Training Accuracy (%)	Training Loss	Validation Accuracy (%)	Validation Loss	Testing Accuracy (%)
CNN	46	94	0.17	73	1.16	74
ResNet	50	93	1.167	80	1.1323	82
DenseNet201	20	90	0.8312	82	0.8312	83
After Fine-tunning	20	99.12	0.0267	86.69	0.62	87.724

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