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Image Processing & Autoencoder Boost Two-Stage Filtering For Pigmented Skin Lesion Detection

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Abstract

It is critical to diagnose pigmented skin lesions, which might be benign or malignant, as early as possible. For better detection, this paper suggests a two-stage filtering method that is followed by majority voting. In stage 1 filtering Hough line transformation, morphological operations, and Canny edge detection are some of the image processing techniques used to remove hair. Stage 2 filtering uses a convolutional autoencoder to extract features and reduce noise even more. Through majority voting, combined predictions from deep learning (CNN) and machine learning (Random Forest) models, both trained on the massively filtered dataset (HAM10000), are blended to produce results that are more accurate than those of the individual models. This ensemble approach demonstrates promising potential for AI-powered primary care diagnosis of pigmented skin lesions, aiding early and precise identification.

Keywords: *Autoencoder, Majority-voting, Random Forest, CNN, Skin Lesions.*

1 Introduction

1.1 Pigmented Skin Lesions: Pigmented skin lesions are skin areas that have a different color or texture than the surrounding skin. Various factors, such as melanin, blood, or exogenous pigment, can cause pigmented skin lesions. There are four main types of pigmented skin lesions: m[1]elanocytic, keratinocytic, vascular, and reactive [17]. Melanocytes, the cells that produce melanin, give rise to melanocytic lesions. Melanin is the pigment that gives skin its color. Melanocytic lesions can be benign or malignant. Benign melanocytic lesions include moles, freckles, and birthmarks. Malignant melanocytic lesions include melanoma, a type of skin cancer that can be deadly if not detected and treated early. Keratinocytes, the cells that make up the outer layer of the skin, give rise to keratinocytic

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lesions. Keratinocytes can also produce some melanin, which can result in pigmented lesions. Keratinocytic lesions can be benign or malignant. Benign keratinocytic lesions include seborrheic keratosis, lentigo, and epidermal naevus. Malignant keratinocytic lesions include basal cell carcinoma, squamous cell carcinoma, and actinic keratosis. Vascular lesions can be benign or malignant. Benign vascular lesions include cherry angioma, angiokeratoma, and purpura. Malignant vascular lesions include angiosarcoma and Kaposi sarcoma. Reactive pigmentation is a response to inflammation, injury, or infection of the skin. It can result in a darkening or lightening of the skin color. Reactive pigmentation can be temporary or permanent. Examples of reactive pigmentation include dermatofibroma, postinflammatory pigmentation, and lichen planus.

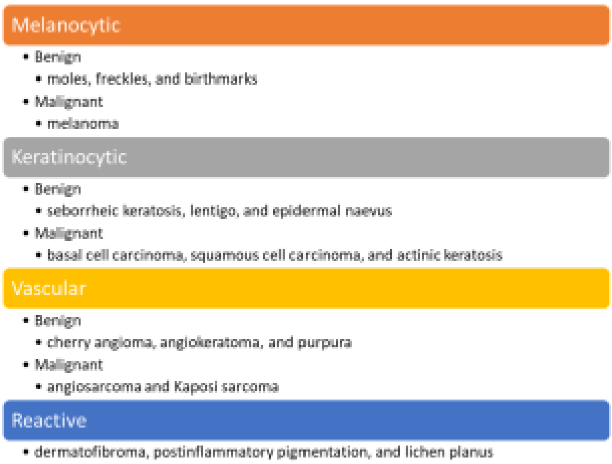


Figure 1: Various types of skin lesions.

1.2 HAM 10000 Dataset: The HAM10000 dataset is a collection of dermatoscopic images used for research in the field of dermatology and machine learning. Keep in mind that there may have been updates or changes since then. The dataset contains a total of 10,015 dermatoscopic images [22]. These images are categorized into seven different diagnostic categories, representing various skin conditions and lesions. The classes are Melanocytic nevi (nv), Melanoma (mel), Benign keratosis-like lesions (bkl), Basel cell carcinoma (bcc), Actinic keratosis and Intraepithelial carcinoma (akiec), Dermatofibroma (df) and Vascular (vasc) lesions. The dataset is annotated with diagnostic information for each image, indicating the category of skin lesion. HAM10000 has been widely used in machine learning research, especially in the development and evaluation of algorithms for the automatic classification of skin lesions. Like many medical image datasets, HAM10000 may have class imbalances, where certain classes have more examples than others.

Figure 2: All seven types of pigmented skin lesions.

The HAM10000 dataset is publicly available and can be downloaded from the ISIC archive. It is a valuable resource for researchers who are developing machine learning algorithms for the detection and classification of skin lesions. The Table 1 shows the count of images with respect to each type.

Type	Images count
akiec	327
bcc	514
bkl	1099
df	115
mel	1113
nv	6705
vasc	142

Table 1: Category wise count of images

1.3 Machine Learning and Deep Learning Models: Support Vector Machines (SVMs) are a powerful class of supervised machine learning algorithms used for classification and regression tasks [6]. In the context of image classification, SVMs can be employed to distinguish between different classes of images based on their features. SVMs have been widely used for image classification, especially in scenarios with relatively small to medium-sized datasets. In recent years, deep learning methods, particularly CNNs, have gained prominence in image classification tasks, often outperforming traditional machine learning approaches like SVMs [4, 5]. However, SVMs remain a valuable tool in situations where interpretability and a clear decision boundary are crucial. SVM models are less prone to overfitting and noise compared to other algorithms. Training SVMs, especially with large datasets and complex kernels, can be time-consuming. Selecting optimal parameters like the kernel type and margin requires careful grid search and experimentation.

Random Forest is an ensemble learning method that can be used for both classification and regression tasks. In the context of classification, Random Forest builds multiple decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random Forests offer several advantages, including high accuracy, resistance to overfitting, and the ability to handle large datasets with high dimensionality. They are also robust to noisy data and outliers. These qualities make Random Forest a popular choice for classification tasks in various domains, including image classification, where they can effectively handle complex relationships in the data [6, 7].

Various Convolutional Neural Network (CNN) models have been developed for image classification tasks, each with its own architecture and characteristics. These models are pre-trained on massive datasets like ImageNet, learning generic features that can be applied to new tasks. This transfer learning approach allows you to fine-tune the models for your specific image classification problem with less data and training time [8, 9].

VGG16 & VGG19: The VGG (Visual Geometry Group) networks were proposed by the Visual Geometry Group at the University of Oxford. VGG16 and VGG19 are named after the number of weight layers they have. The original workhorse, featuring 16 layers of hidden units, offering a good balance of accuracy and efficiency. Ideal for smaller datasets or resource-constrained environments [9]. VGG16's bigger brother VGG19, boasting 19 layers and even higher accuracy. But with greater power comes greater responsibility – it requires more data and computational resources. Both VGG architectures consist of a series of convolutional layers with small 3x3 filters, followed by max-pooling layers. The use of small filters allows the networks to capture complex patterns in the data. VGG networks are known for their simplicity and uniform architecture, making them easy to understand and implement. They are effective for image classification tasks and have been widely used as a baseline architecture.

ResNet50: ResNet (Residual Network) was introduced to address the challenge of training very deep neural networks. ResNet50 is a variant of the ResNet architecture with 50 layers. Training very deep networks can become challenging, with vanishing gradients hindering learning. Enter ResNet50, the revolutionary architecture that introduced skip connections. These connections bypass layers, directly feeding information from earlier stages to later ones, alleviating the vanishing gradient problem and enabling deeper, more accurate models. ResNet architectures have achieved state-of-the-art results in various image classification and computer vision tasks. The residual connections enable the training of deeper networks without suffering from degradation in performance [10].

InceptionV3: InceptionV3, part of the Inception family of models (also known as GoogLeNet), was developed by Google. It is designed to be computationally efficient while capturing intricate features in the data. InceptionV3 employs inception modules, which use multiple filter sizes (1x1, 3x3, and 5x5) in parallel to capture information at different scales. It also includes auxiliary classifiers at intermediate layers to promote the flow of gradient during training. InceptionV3 is known for its performance and has been widely used in various applications, including image classification, object detection, and more [19, 20].

2 Results and Discussion

2.1 Data Collection: To begin collecting data, we obtained the HAM10000 dataset from the ISIC database and organized the images into directories according to the skin lesion types, as shown in the figure 3.

Figure 3: Directory organization of images with respect to type of skin lesions.

2.2 Stage 1 Filtering: To remove the hair content from the images we used the following image processing tasks on each image.

i. Convert the image to grayscale.
ii. Detect the edges using Canny edge detection.
iii. Morphologically close and erode the edges.
iv. Use Hough line transform to identify the coordinates of the edges.
v. Discard the edges and lines that are too short or too long.
vi. Using the coordinates of the lines create a mask.
vii. Dilate the mask to cover more areas for robust interpolation.
viii. Interpolate the pixels in the mask using the median of the neighboring pixels.

After converting the input color image to grayscale Canny edge detection algorithm is applied to identify the edges in the grayscale image [11]. This step is crucial for identifying the boundaries between different structures, such as hair and skin. Morphological operations closing helps to connect gaps in the edges, while erosion can help refine and thin the edges, making them more precise. Hough line transform is used to identify lines in the processed image [12]. In the context of hair removal, this can help detect prominent linear structures, which may correspond to strands of hair. Filter out lines that are either too short or too long helps to eliminate spurious lines and focus on hair strands of a reasonable length. Then a binary mask is generated, marking pixels along identified hair lines. This mask represents the areas of the image that are likely to contain hair. Dilate the mask to expand the regions of interest ensures that the areas around the detected hair edges are covered more broadly for subsequent processing, making the removal more robust. Applying pixel interpolation to estimate pixel values within the masked regions using the median of neighboring pixels helps smooth out the interpolation and reduce the impact of outliers, resulting in a more natural-looking transition between the hair and skin areas. Figure 4 shows the intermediate results at various stages of stage 1 filtering. The various parameters used in various stages of this filtering are: in Canny Edge Detection minVal threshold 200 and maxVal threshold 220, in Hough Line Transform rho 1, theta 1, threshold for voting 50, minTheta 1 and maxTheta 30.

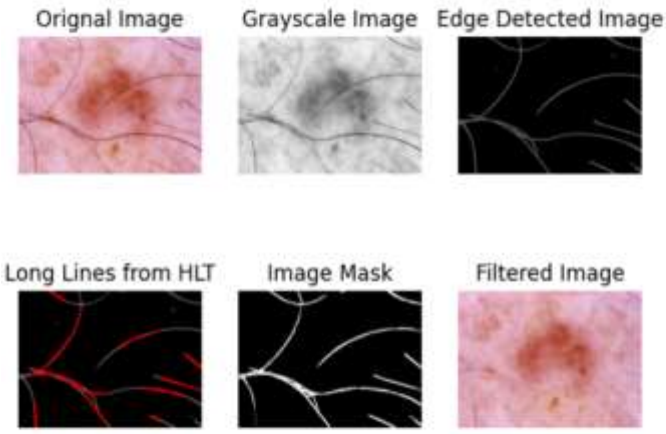


Figure 4: Stage-1 Filtering results.

2.3 Stage 2 Filtering: In stage 2 we used a Convolutional Autoencoder (CAE) to get more filtering on the output of the stage 1 output images. CAE is one of the best choices for noise removal from images [14 – 16]. Here we used a simple CAE with 5 convolution, 2 max-pooling and 2 up-sampling layers. The structure of the CAE used in stage 2 with the dimensions of intermediate outputs is shown in the figure 5.

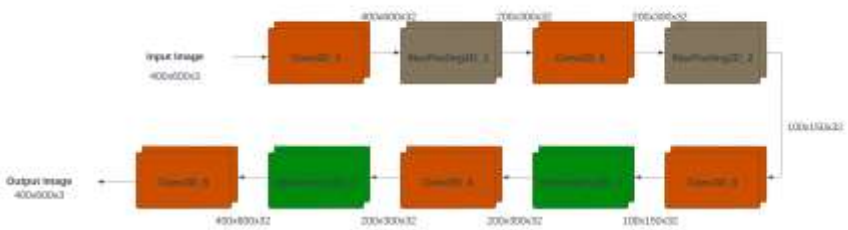
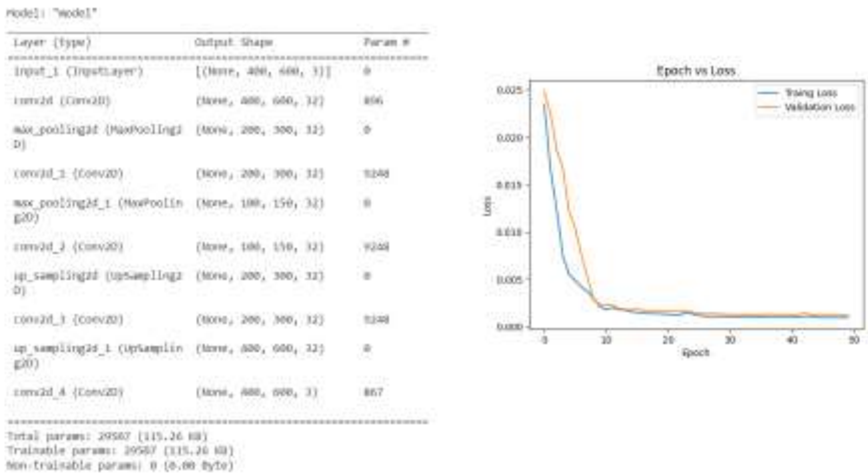


Figure 5: Various layers of Convolutional Autoencoder used in stage 2 filtering.

To train the CAE we have taken the help of stage 1 filter. We have taken total 481 images containg some hair in them, appled them to stage 1 filter and its output is taken as target for training CAE. The CAE model summary and reduction in the loss withrespect to epochs is sown in the Figure 6. Here the measure of the loss considered is MSE.



Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 400, 600, 3)]	0
conv2d (Conv2D)	(None, 400, 600, 32)	896
max_pooling2d (MaxPooling2D)	(None, 200, 300, 32)	0
conv2d_1 (Conv2D)	(None, 200, 300, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 100, 150, 32)	0
conv2d_2 (Conv2D)	(None, 100, 150, 32)	9248
up_sampling2d (UpSampling2D)	(None, 200, 300, 32)	0
conv2d_3 (Conv2D)	(None, 200, 300, 32)	9248
up_sampling2d_1 (UpSampling2D)	(None, 400, 600, 32)	0
conv2d_4 (Conv2D)	(None, 400, 600, 3)	867

Total params: 29507 (115.26 KB)
Trainable params: 29507 (115.26 KB)
Non-trainable params: 0 (0.00 Byte)

Figure 6: a) CAE layer wise summary b) Training loss and Validation loss with number of epochs.

The result of two stage filtering is shown in the figure 7. Which clearly indicates subjectively a filtering with the both the stages can be obtained to remove hair content from the input images.

Figure 7: a) Input image   b) Filtered image after stage 1   c) Filtered image after stage 2

To train the deep learning models images are resized to 400 X 600 pixels and then divided in to training and validation subsets with 90:10 proportion. Then we got training set with 9014 images and validation set with 1001 images. The code snippet of this splitting is shown in the figure 8.

```
train_ds, val_ds = image_dataset_from_directory(r"D:\Misc\databases\HAM10000\dataset",
                                                label_mode='categorical',
                                                image_size=(400, 600),
                                                seed=19,
                                                validation_split=0.1,
                                                subset="both",
                                               )
```

```
Found 10015 files belonging to 7 classes.
Using 9014 files for training.
Using 1001 files for validation.
```

Figure 8: Number of images in training and validation sets after splitting in 90:10 ratio.

2.4 Model Development and Results: SVM and Random Forest models are trained using training image subset without and with filtering. With original images SVM has given an accuracy of 69.44% and Random Forest has given 71.44% accuracy. After removing hair content using both the stages of filtering there is no improvement in the accuracy of SVM (69.29%) and a slight improvement with Random Forest (71.69%). The confusion matrices of both the models are shown in the following figure 9.

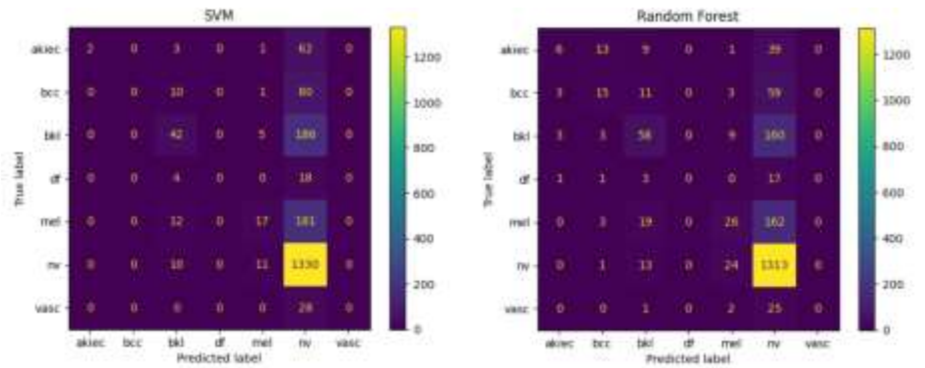


Figure 9: Confusion matrices obtained in the evaluation of SVM and Random Forest models

We used transfer learning and trained the top layers of VGG16, VGG19, ResNet50 and Inception models for the classification of skin lesion images [8], with filtered images obtained accuracies are 83.23%, 80.44%, 83.45% and 67.56% respectively. Among all four models we observed best accuracy (83.45%) from the ResNet50. Since we obtained good performance from Random Forest, VGG16, VGG19, and ResNet50. Hence we combined the predictions of them and then we consider the final prediction based on majority voting as shown in the below figure 10. Which has given the accuracy of 87.55%.

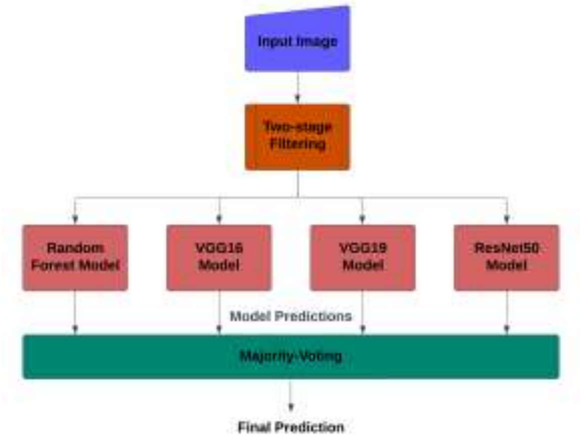


Figure 10: Proposed Majority-voting based model.

The figure 11 shows the confusion matrix obtained by the proposed model, in which the predictions from Random Forest, VGG16, VGG19 and ResNet50 are given as inputs to a majority-voting block to get final prediction.

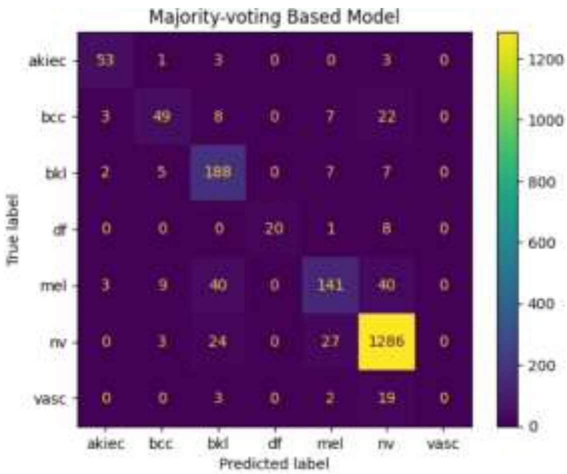


Figure 11: Confusion matrix of proposed model

The following table 2 shows the model used and their accuracies without using filtering and after using 2-stage filtering to remove hair content.

Model	**Accuracy without any filtering**	**Accuracy with 2-stage filter**
SVM	69.44%	69.29%

Random Forest	71.43%	71.69%
VGG16	73.23%	83.23%
VGG19	72.43%	80.44%
ResNet50	75.62%	83.45%
InceptionV3	67.38%	67.56%
Proposed Majority-voting based model	82.3%	87.55%

Table 2: Models and their accuracies.

In this work we successfully developed a new majority-voting based model for skin lesion classification, achieving an accuracy of 87.55%. This model outperforms existing models and demonstrates the effectiveness of combining different models to improve classification performance.

3 Conclusion: In conclusion, this research paper presents a novel approach for the primary diagnosis of pigmented skin lesions using a majority-voting-based ensemble method. The study employed machine learning and deep learning models, including SVM, Random Forest, VGG16, VGG19, ResNet50, and Inception, on the HAM10000 dataset after removing hair content using two-stage filtering. The first stage of filtering involves a series of image processing tasks to eliminate hair content, while the second stage employs a Convolutional Autoencoder (CAE) for additional noise removal. While individual models demonstrated varying accuracies, the combination of Random Forest, VGG16, VGG19 and ResNet50 through majority voting yielded a notable improvement, achieving an accuracy of 87.55%. The results suggest that the ensemble of diverse models can enhance the accuracy of pigmented skin lesion classification, providing a promising avenue for primary diagnosis in clinical settings. This approach holds potential for contributing to more accurate and reliable identification of benign and malignant lesions, aiding clinicians in determining appropriate treatment courses for patients.

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