COMPUTER VISION PROJECT 1 - SKIN LESION CLASSIFICATION

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Abstract

This report describes the implementation for the Classification of dermoscopic images into melanoma and melanocytic nevus. The proposed approach combines classical image processing techniques, feature extraction, and a supervised machine learning classifier. The focus of this project was to extract vector features from images and manually run them on a simple ML model. It was decided to follow this path rather than using a CNN model.

1 Dataset

The experiments are conducted using the ISIC 2019 dataset, a publicly available benchmark for skin lesion analysis. Only images belonging to the classes *melanoma* and *melanocytic nevus* are considered, in accordance with the project specifications.

The dataset consists of high-resolution RGB dermoscopic images acquired under heterogeneous lighting conditions. As a consequence, dedicated preprocessing and normalization steps are required to reduce variability unrelated to the lesion itself.

2 Pipeline Overview

The implemented pipeline of project is composed of the following stages:

- Image denoising
- Lesion segmentation
- Post-segmentation enhancement
- Feature extraction
- Feature normalization
- Classification

Each stage is implemented as an independent module, allowing incremental testing and debugging.

3 Image Preprocessing

Preprocessing is divided into two distinct phases.

Before segmentation, a denoising operation is applied to the input RGB image using a median filter. This filter is effective in reducing impulsive noise and small artifacts, such as hair or sensor noise, while preserving lesion boundaries.

After segmentation, preprocessing is applied exclusively to the lesion region. Contrast enhancement is performed using Contrast Limited Adaptive Histogram Equalization (CLAHE) on the L channel of the LAB color space. Restricting this operation to the segmented lesion avoids altering background regions and improves the stability of the extracted features.

4 Lesion Segmentation

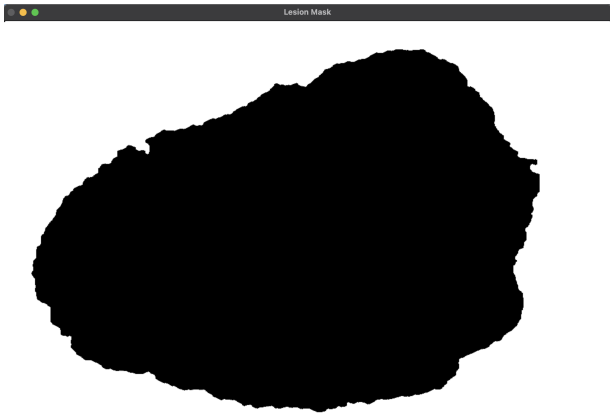
Lesion segmentation aims to isolate the lesion from the surrounding healthy skin. The image is converted to the HSV color space, and the saturation channel is selected to emphasize the contrast between lesion and background.

Automatic thresholding is performed using Otsu's method. Morphological operations are subsequently applied to remove small spurious regions. Finally, the largest connected component is selected as the lesion mask, ensuring robustness against segmentation noise.

Below, three images are shown starting from the original at the end of the segmentation and preprocessing process:

4.1 Original Image

4.2 Lesion Mask



4.3 Processed Lesion

5 Feature Extraction

After segmentation, a set of quantitative features is extracted to describe the lesion. The features are grouped into shape, color, and texture descriptors.

5.1 Shape Features

Shape features describe the geometric properties of the lesion and include:

- Area
- Perimeter
- Circularity
- Eccentricity
- Solidity

These features are clinically relevant, as malignant lesions often exhibit irregular borders and asymmetric shapes.

5.2 Color Features

Color features are computed in the LAB color space to reduce sensitivity to illumination variations. For each channel (L, A, B), the mean and standard deviation are computed over the lesion region only.

5.3 Texture Features

Texture features are extracted from the grayscale representation of the lesion. A simplified Local Binary Pattern (LBP) descriptor is computed by comparing each pixel with its 8 neighbors. The normalized histogram of LBP values is used as a texture descriptor.

In addition, a simple contrast feature is computed as the difference between the maximum and minimum grayscale intensities within the lesion. These features provide complementary information about lesion heterogeneity.

6 Feature Dataset Construction

For each image, the extracted shape, color, and texture features are concatenated into a single feature vector. All feature vectors are assembled into a feature matrix, while the corresponding class labels are stored in a separate array.

This representation enables the use of standard machine learning algorithms and allows efficient training and evaluation.

7 Train-Test Split and Normalization

The dataset is divided into training and test sets using a stratified splitting strategy in order to preserve the class distribution.

The rateo of split is: 70% training set and 30% test set

Feature normalization is performed using Z-score standardization. The mean and standard deviation are computed exclusively on the training set to avoid data leakage. Both training and test features are normalized using the same statistics.

8 Classification Model

Classification is performed using a Multi-Layer Perceptron implemented in PyTorch. The network consists of three hidden layers with 128, 64, and 32 neurons, each followed by a ReLU activation function. A single output neuron produces a logit representing the probability of malignancy.

Binary Cross-Entropy loss with logits is used during training. To address class imbalance, a positive class weighting strategy is employed, assigning higher importance to melanoma samples.

9 Training and Evaluation

The model is trained using the Adam optimizer with a fixed learning rate. Mini-batch training is performed with a batch size of 64 to improve convergence stability.

The training process is carried out for 100 epochs. Model performance is evaluated on a held-out test set using classification accuracy, providing a clear measure of generalization performance.

10 Results

In conclusion of the report, the results obtained through this project are shown, using a model as simple and light as possible. Future work of this project may include the integration of additional texture descriptors or the use od depp learning models for segmentations.

```
Features matrix: (17397, 20)
Labels: (17397,)
Train set: (12179, 20)
Test set: (5218, 20)
Epoch 10/100 - Loss: 0.6181
Epoch 20/100 - Loss: 0.5351
Epoch 30/100 - Loss: 0.4512
Epoch 40/100 - Loss: 0.3842
Epoch 50/100 - Loss: 0.3108
Epoch 60/100 - Loss: 0.2523
Epoch 70/100 - Loss: 0.2227
Epoch 80/100 - Loss: 0.1673
Epoch 90/100 - Loss: 0.1255
Epoch 100/100 - Loss: 0.0977
Accuracy: 0.8031812906265259
```

References

[1] ISIC Archive. Skin Lesion Images for Melanoma Classification. https://www.kaggle.com/datasets/andrewmvd/isic-2019?resource=download