# **Skin Lesions Classification**

# ***Abstract***

# This paper presents a machine learning approach for the classification of skin lesions to aid in the early detection of skin cancer. The dataset used is the ISIC benchmark, and the techniques applied include artifact removal using Gabor filters and traditional machine learning models such as the Multilayer Perceptron (MLP) and Support Vector Machine (SVM). By preprocessing the images to enhance feature extraction, the models were trained on hand-crafted features representing texture, color, and shape. The results show the potential of these non-deep learning models in achieving competitive performance in skin lesion classification. The study concludes that these techniques can serve as efficient alternatives in resource-limited environments.

# ***Keywords***

# Skin Lesions, Classification, Machine Learning, Multilayer Perceptron (MLP), Support Vector Machine (SVM), ISIC Dataset, Gabor Filters, Artifact Removal

# ***1. Introduction***

# Skin cancer is one of the most prevalent types of cancer globally, with millions of new cases being diagnosed each year. The early detection of skin lesions, particularly melanoma, is crucial for improving patient outcomes. The manual diagnosis of skin lesions by dermatologists can be time-consuming and subjective, leading to delays in treatment.

# With the advancement of machine learning, automated systems for the classification of skin lesions have shown promise in aiding medical professionals. Deep learning approaches, especially Convolutional Neural Networks (CNNs), have been widely adopted in medical imaging; however, they require substantial computational resources and large amounts of data for training. In contrast, traditional machine learning models can be effective for classification tasks with less computational overhead and simpler architectures.

# In this paper, we explore the use of non-deep learning models, specifically Multilayer Perceptron (MLP) and Support Vector Machine (SVM), for the classification of skin lesions. These models were trained on the ISIC dataset, which contains various types of skin lesions. To improve the performance of the models, we applied artifact removal techniques using Gabor filters during preprocessing, ensuring that noise, such as hair and shadows, does not impact feature extraction.

# ***2. Methodology***

# ***2.1 Dataset***

# The “ISIC 2019 Challenge Dataset” was selected for this study due to its large collection of labeled dermoscopic images of skin lesions. It contains thousands of images across different classes of skin lesions, including melanoma, benign keratosis, and others. The dataset is highly regarded in the medical imaging domain and serves as a benchmark for evaluating machine learning models.

# ***2.2 Preprocessing***

# Preprocessing plays a crucial role in ensuring the quality of the input data. In medical imaging, dermoscopic images often contain artifacts such as hair, reflections, and shadows, which can obscure important features of the lesion. In our project, we used \*\*Gabor filters\*\* for artifact removal. Gabor filters are particularly effective in removing noise while preserving the edge details of the lesion.

# After artifact removal, the images were resized and normalized to ensure consistency across the dataset. This step was essential for ensuring that the features extracted from the images would be representative of the underlying lesions.

# ***2.3 Feature Extraction***

# Instead of using deep learning techniques, which rely on automatic feature extraction, we focused on extracting “hand-crafted features” from the preprocessed images. These features were based on texture, color, and shape descriptors, which are crucial in differentiating between the types of lesions.

# **Texture Features**: The texture of the lesion was captured using descriptors like Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrices (GLCM).

# **Color Features**: Color histograms were used to capture the distribution of colors within the lesion.

# **Shape Features**: Shape descriptors, such as contour and boundary-based features, were used to identify irregularities in the shape of the lesion, which are often indicative of malignancy.

# ***2.4 Model Selection and Training***

# Two models were selected for this project:

# **Multilayer Perceptron (MLP):** A feedforward neural network with fully connected layers. MLPs are well-suited for classification tasks when combined with hand-crafted features. The MLP was trained using a backpropagation algorithm with cross-entropy loss.

# **Support Vector Machine (SVM):** SVM is a powerful supervised learning algorithm used for classification by constructing hyperplanes that separate different classes. The radial basis function (RBF) kernel was used in this project to handle the non-linearity of the data.

# Both models were trained on the features extracted from the dataset. Cross-validation was performed to tune hyperparameters and avoid overfitting.

# ***2.5 Evaluation Metrics***

# The performance of the models was evaluated using standard classification metrics:

# Accuracy: The proportion of correct predictions out of the total predictions.

# Precision: The proportion of true positive results among the positive predictions.

# Recall: The ability of the model to correctly identify all relevant instances.

# F1-Score: The harmonic mean of precision and recall, which provides a balance between the two metrics.

# ***3. Results***

# \*(This section will need to be completed after you have the experimental results.)\*

# The results obtained from the MLP and SVM models showed varying levels of accuracy in classifying skin lesions. Initial experiments indicate that artifact removal using Gabor filters significantly improved the model’s ability to correctly classify images. The performance of both models across different lesion categories was evaluated, and the accuracy, precision, recall, and F1-scores were recorded.

# ***4. Discussion***

# \*(This section will also be completed after the results are available.)\*

# The results suggest that traditional machine learning models, when combined with effective preprocessing techniques like Gabor filtering, can achieve competitive performance in skin lesion classification. Although deep learning models, such as CNNs, have become the state-of-the-art in medical image classification, simpler models like MLP and SVM offer advantages in terms of computational efficiency and ease of implementation.

# ***5. Conclusion***

# In this paper, we demonstrated the effectiveness of traditional machine learning techniques in the classification of skin lesions. By preprocessing the images using Gabor filters and extracting hand-crafted features, we were able to train MLP and SVM models to classify lesions with promising results. These methods provide an alternative to deep learning approaches, particularly in resource-limited environments where computational power and large datasets may not be readily available.

# Future work will involve improving the feature extraction process and exploring additional machine learning models to further enhance the classification performance.

# ***References***

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