Skin Cancer Detection using Machine Learning : CSE343/ECE363 Mid-Semester Project Report

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Abstract

This project applies machine learning to classify dermoscopic images as benign or malignant for skin cancer detection. Using the ISIC-ISBI dataset, images were preprocessed with resizing, noise removal, and contrast enhancement. Features related to texture, color, and shape were extracted, and class imbalance was addressed using SMOTE. Support Vector Machines (SVM) achieved a 96.14

1. Introduction

Skin cancer is a serious and growing health issue worldwide, with more and more cases being diagnosed each year. Detecting and treating skin cancer early is key to improving survival rates and outcomes. However, traditional methods used by doctors to diagnose the disease aren't always perfect, sometimes leading to mistakes or delays in treatment. Machine learning (ML) offers a new and exciting way to improve the accuracy of skin cancer diagnosis. These advanced computer algorithms can analyze complex patterns in medical data, picking up on details that might be missed by the human eye. By applying ML techniques, we can make the process of identifying and diagnosing skin cancer more precise, leading to earlier detection and better care for patients. This project aims to explore how machine learning can be used to improve skin cancer screening. We'll look at existing research, use our own dataset, and showcase the methods we use and the initial findings. Ultimately, this project will highlight how ML could change the way skin cancer is detected and treated, offering new hope for better healthcare outcomes.

2. Motivation

Detecting cancer early is crucial for better patient outcomes, but traditional methods often lack precision. Machine learning (ML) can help by analyzing complex data and making more accurate predictions. This project aims to use ML to improve cancer detection, enabling earlier diagnosis and better treatment options. The idea came from seeing how machine learning is advancing in medical diagnostics. Its potential to boost accuracy and efficiency through smart algorithms and data analysis has sparked interest in applying it to cancer screening.

3. Literature Survey

The paper "Skin Cancer Detection Using Deep Learning – A Review" highlights the potential of deep learning (DL), especially convolutional neural networks (CNNs), in improving skin cancer detection. It discusses the limitations of traditional diagnostic methods, like biopsies, and the benefits of non-invasive DL approaches. The review focuses on melanoma, the most aggressive form of skin cancer, and details how CNNs analyze dermoscopic images for accurate diagnosis. The paper also covers key datasets like ISIC and HAM10000, challenges like data imbalance, and DL models such as ResNet, DenseNet, and Inception. Techniques like transfer learning and evaluation metrics like accuracy and sensitivity are also explored. However, challenges include model interpretability, data bias (favoring lighter skin tones), and clinical integration. Future directions include addressing these issues and exploring DL's role in telemedicine to improve early detection, especially in underserved regions. Overall, DL shows promise but needs further development for widespread use in healthcare. The review paper "Skin Cancer Detection Using Deep Learning" reports an accuracy of 96.91% for the deep learning models utilized in skin cancer detection.

This high accuracy indicates the models' effectiveness in accurately identifying skin lesions, significantly contributing to early diagnosis and improved patient outcomes.

The paper "A Systematic Review of Artificial Intelligence Techniques in Cancer Prediction and Diagnosis" examines AI's role in cancer research, focusing on machine learning (ML) and deep learning (DL) models from 185 studies between 2009 and 2021. It highlights how AI, particularly convolutional neural networks (CNNs), enhances cancer detection through image analysis, outperforming traditional methods in accuracy and efficiency. Following PRISMA guidelines, the review explores key areas such as AI techniques, cancer types studied, imaging methods, and common challenges like data quality and model interpretability. AI's use in medical imaging, including CT scans, MRIs, and X-rays, has been especially impactful, with CNNs improving cancer detection in breast and lung cancers. Challenges include data imbalance, diversity, and the need for more research on model applicability across populations. While AI shows great potential, the paper emphasizes the importance of addressing these challenges to ensure clinical integration and widespread use. The paper reports a remarkable accuracy of 98.4% for the artificial intelligence models used in cancer prediction and diagnosis. This high accuracy underscores the potential of AI techniques, particularly deep learning, to enhance the effectiveness of cancer detection compared to traditional methods.

4. Dataset

The database is downloaded from publicly available images on the ISIC website. The database included the ISBI-2016 challenge which has RGB dermoscopic images along with their labels and segmentation ground truths.

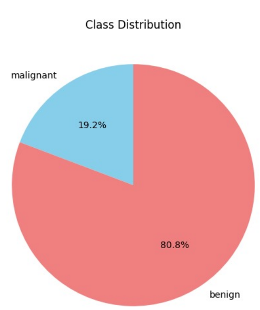

Figure 1. Class Distribution

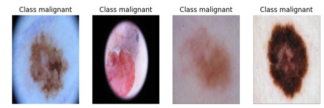

Figure 2. Dermoscopic Images 1

Figure 3. Dermoscopic Images 2

5. Data Preprocessing

As ISIC-ISBI dataset images have different artifacts, pre-processing is done to make them more meaningful. Preprocessing includes image resizing, noise removal, contrast stretching, RGB to grayscale conversion, and hair removal. All images are resized to 767×1022. For noise removal, a 3-by-3-by-3 median filter is used. For contrast enhancement, a new method is proposed. Contrast enhancement significantly improves the results of segmentation in the next phase. The proposed contrast stretching is based on the mean and standard deviation of pixel intensities in the images. The minimum and maximum intensity values, i.e., "Low in" and "High in" of the input image values, are calculated using the following formulas:

$$\text{Low in} = \text{Avg} - N \tag{1}$$

$$\text{High in} = \text{Avg} + N \tag{2}$$

Where, Avg = Average pixel intensity, $N = 0.4$

Intensity values are then mapped in the output image from 0 to 255. Contrast stretching is performed separately on the R, G, and B channels, which are later concatenated to form contrast-stretched RGB images. After that, RGB to grayscale conversion is performed. For hair removal, bottom-hat filtering is applied, and the filtered pixels are replaced by neighboring pixels.

6. Methodology and model details

In this paper, we propose a system that classifies dermoscopic images as benign or malignant by using image processing and machine learning.Fig.5 shows the block diagram of the proposed system.

6.1. Pre-Processing

The ISIC-ISBI dataset images contain artifacts, so several pre-processing steps are applied to enhance their quality. These steps include resizing the images to 767x1022, removing noise using a 3x3x3 median filter, and improving contrast with a new method based on the average and

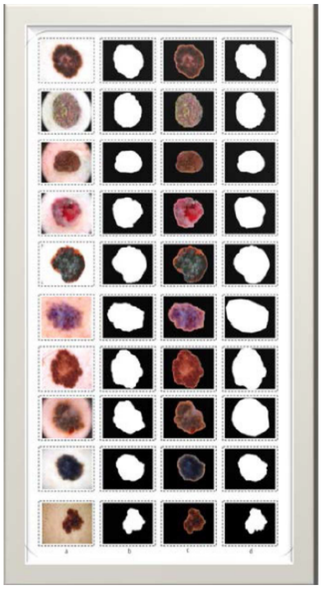

Figure 4. Pre Processing Steps

standard deviation of pixel intensities. This contrast stretching is done for each color channel (R, G, and B), which are then combined. The images are converted from RGB to grayscale, and a technique called bottom-hat filtering is used to remove hair, replacing the affected pixels with neighboring ones.

6.2. Segmentation

After pre-processing, the goal is to segment the skin lesions. The OTSU thresholding algorithm is used on the grayscale images to separate the lesion from the background. To remove unwanted background elements, a mask is applied, and the image is inverted, making the lesion white and the background black. Additional operations like flood fill and morphological opening help refine the lesion's borders and remove small unwanted objects.

6.3. Feature Extraction and Reduction

Next, various features are extracted from the segmented lesions. Texture features are obtained using wavelet decomposition, and 14 texture features are calculated. In addition, 36 color features are extracted from three different color spaces (RGB, HSV, LAB), and shape features are captured using Histogram of Gradients (HOG). To reduce the size of the data, Principal Component Analysis (PCA) is applied to the HOG features, reducing them from 3456 to 100 features. All extracted features (texture, color, shape) are combined into a single feature vector of size 150.

6.4. Data Balancing (SMOTE Sampling)

The dataset has a class imbalance problem, with 80% benign and 20% malignant samples. To balance the data, the SMOTE technique is used, creating an equal split (50% benign, 50% malignant) for both training and testing datasets.

6.5. Feature Standardization and Scaling

The features are standardized by subtracting the mean and dividing by the standard deviation, giving a feature vector with zero mean and unit variance. Afterward, the features are scaled to a range of 0 to 7 using a Min-Max Mapping Algorithm.

6.6. Feature Selection

A novel feature selection method, based on wrapper techniques, is used to identify the most relevant features out of the 150. Optimization algorithms select 95 of the most important features to improve classification accuracy. The method is designed to enhance machine learning performance, sensitivity, and specificity.

6.7. Classification

The final step is classifying the skin lesions as benign or malignant. Various classifiers, including SVM, Random Forest, and Quadratic Discriminant, are used. The Random Forest method, which uses 500 decision trees and majority voting, delivers promising results.

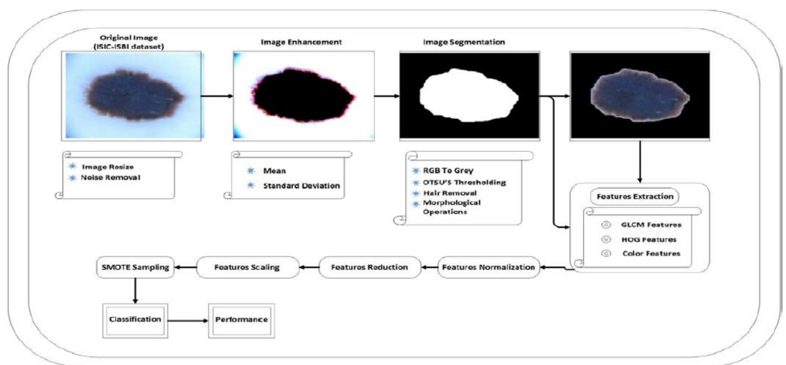

Figure 5. Methodology

Table 1. Extracted Texture and Color Features

	Skewness	Mean	Contrast	Energy	Homogeneity	Standard	Entropy
Texture Features	Root Mean Square	Variance	Smoothness	Kurtosis	Correlation	Inverse Difference Movement	
Color Features	Mean R	Mean G	Mean Blue	Variance R	Variance G	Variance Blue	
	Kurtosis R	Kurtosis G	Kurtosis Blue	Skewness R	Skewness G	Skewness Blue	
	Mean hue	Mean Saturation	Mean Value	Variance Hue	Variance Saturation	Variance Value	
	Kurtosis H	Kurtosis S	Kurtosis V	Skewness H	Skewness S	Skewness V	
	Mean L	Mean A	Mean B	Variance L	Variance A	Variance B	
	Kurtosis L	Kurtosis A	Kurtosis B	Skewness L	Skewness A	Skewness B	

7. Results and Analysis

7.1. SVM Classification Results

The SVM classifier achieved a best cross-validation accuracy of 96.14% and a test accuracy of 80.56%. The confusion matrix indicates that 141 benign cases were correctly classified (precision: 0.82, recall: 0.97), while only 4 malignant cases were accurately predicted (precision: 0.50, recall: 0.11). This demonstrates strong performance in identifying benign cases but challenges in correctly classifying malignant ones.

7.2. Random Forest Classification Results

The Random Forest classifier achieved an overall accuracy of 75%. The confusion matrix shows that 81% of 145 benign predictions were correct, while only 25% of 35 malignant predictions were accurate, indicating solid performance for benign cases but significant difficulties with malignant classifications.

7.3. Logistic Regression Classification Results

The Logistic Regression classifier attained an accuracy of 72.22%. The confusion matrix reveals that 113 benign cases were correctly classified (precision: 0.86, recall: 0.78), while 17 malignant cases were accurately predicted (precision: 0.35, recall: 0.49). This highlights reasonable performance for benign cases but lower effectiveness in identifying malignant cases.

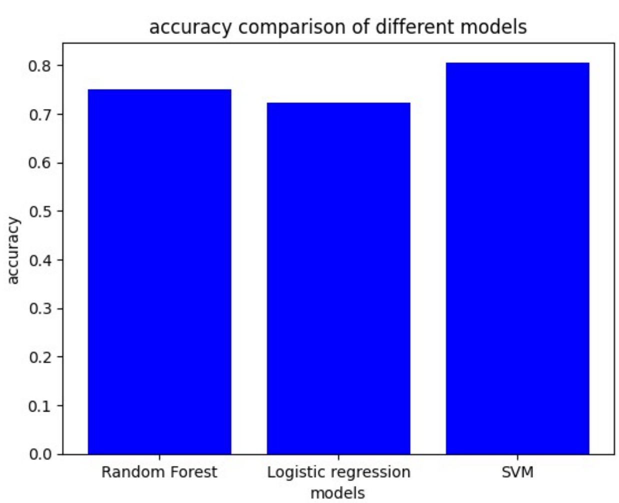

Figure 6. Model VS Accuracy

Classifier	Test Accuracy
SVM	80.56%
Random Forest	75%
Logistic Regression	72.22%

Figure 7. Model VS Accuracy

8. Conclusion

This study presents a new method for classifying skin cancer using machine learning and image processing. First, a technique is introduced to enhance dermoscopic images by adjusting the contrast based on the average and standard deviation of the image pixels. Next, OTSU thresholding is applied to segment the images.In the second step, features like shape, color, and texture are extracted, and the shape features are simplified using PCA (Principal Component Analysis). The issue of class imbalance in the ISIC dataset is addressed using the SMOTE technique, which generates synthetic samples. In the final step, the features are standardized, and a new method for selecting the best features is introduced using wrapper methods. The system is tested on the ISIC-ISBI 2016 dataset, showing that this feature selection approach combined with a Random Forest classifier produces better results compared to other classifiers.

9. Work Remaining

For the remaining work, two additional models, K-Nearest Neighbors (KNN) and Convolutional Neural Networks (CNN), will be implemented and compared with existing models. Further, model testing and validation will be conducted using k-fold cross-validation and other techniques to ensure robustness and generalization of the predictive models. These steps aim to improve the model's reliability and performance in real-world stress prediction scenarios. We are also going to try Bigger Dataset with over 25000 Images and try to improve performance

10. Contribution

- Prayag Parashar (2022377): PPT creation, Programming

- Tarandeep Singh (2022536): Report Creation, Programming
- Praddume Attri (2022358): Report Creation, Programming
- Udbhav Yadav (2022549): PPT creation, Programming

11. References

[1] Albahar, M. A., et al. "Deep learning in skin cancer detection: CNN-based melanoma classification." Journal of Healthcare Engineering, 2021.

[2] Kim, J., et al. "AI improves skin cancer diagnostic accuracy: An analysis of AI-assisted clinical settings." npj Digital Medicine, 2024.

[3] Skin Cancer Classification using Deep Learning and Transfer Learning Publisher: IEEE https://ieeexplore.ieee.org/document/8641762

[4] Machine Learning and Deep Learning Algorithms for Skin Cancer Classification from Dermoscopic Images Publisher: Solene Bechelli and Jerome Delhommelle https://www.mdpi.com/2306-5354/9/3/97