A Machine Learning Approach for Automated Classification of Skin Fungal Infections

Pragya Gupta, Jagannath Nirmal, and Ninad Mehendale*
Department of Electronics and Computer Engineering, K.J. Somaiya College of Engineering, Somaiya Vidyavihar University
Mumbai, India
Email: pragya.g@somaiya.edu, jhnirmal@somaiya.edu, *ninad@somaiya.edu

***Abstract*—Automated classification of skin fungal infections is crucial for accurate diagnosis. This study investigates machine learning for this task using a 1158-image dataset. Preprocessing, feature extraction (texture, structural, statistical), and three feature selection methods (PCA, p-test, top-n) were employed. Five individual classifiers (SVM, Random Forest, Logistic Regression, XGBoost, KNN) and three ensemble methods (Voting, Bagging, Boosting) were evaluated. XGBoost with PCA achieved the highest accuracy of 82%, followed by Voting and Bagging. This study demonstrates the potential of machine learning for automated classification of skin fungal infections.**

I. Introduction

Skin diseases affect a staggering number of people worldwide, with estimates suggesting 4.8 billion new cases annually. Among these, fungal infections pose a significant challenge, accounting for a substantial 34% [1]of all cases. Unfortunately, traditional diagnostic methods like visual examinations can be subjective and susceptible to errors, potentially leading to misdiagnosis and improper treatment [2]. However, advancements in the fields of machine learning and computer vision offer exciting possibilities for the future of dermatology [3]. These technologies hold the potential to revolutionize how we classify skin diseases by enabling automated analysis of medical images [4]. This study delves into this exciting possibility by exploring the feasibility of utilizing machine learning algorithms to differentiate between fungal and non-fungal skin infections from digital images. We leverage a dataset [5] containing 1158 images of skin lesions. To ensure optimal analysis, these images undergo a series of preprocessing techniques, such as adjustments to account for variations in skin tone and the removal of any artifacts. Following preprocessing, we extract various informative features from the images, such as texture patterns, color characteristics, and statistical properties of the lesions. Finally, we evaluate the performance of several machine learning models and ensemble approaches in accurately classifying these infections. Our aim is to contribute valuable insights to the development of more reliable and accessible diagnostic tools for fungal skin infections, ultimately leading to improved patient outcomes.

II. Related Work

Skin cancer classification has witnessed remarkable advancements with machine learning, achieving dermatologist-level accuracy [3]. In identifying fungal infections, computer vision holds promise for enabling swift and precise diagnosis of conditions like ringworm (tinea corporis) and athlete's foot (tinea pedis) [6]. These algorithms analyze distinct patterns associated with fungal proliferation on the skin, aiding clinicians in differentiating fungal infections from other skin conditions [7]. However, fungal infections have not received the same level of attention as skin cancer in machine learning research, which has achieved dermatologist-level accuracy. Existing studies highlight the potential of image processing and machine learning but emphasize the need for more sophisticated algorithms [8]. This gap in research motivates our study, aiming to explore the feasibility of using advanced machine learning for automated classification of fungal infections. We leverage feature engineering techniques like texture analysis and feature selection methods to extract the most informative details from medical images. Additionally, we utilize ensemble learning approaches to combine the strengths of multiple classifiers. Our study seeks to bridge the gap and improve diagnostic accuracy through innovative machine learning techniques.

III. Methodology

This section describes the methodology of this study. Fig 1 depicts the overall methodology for this study.

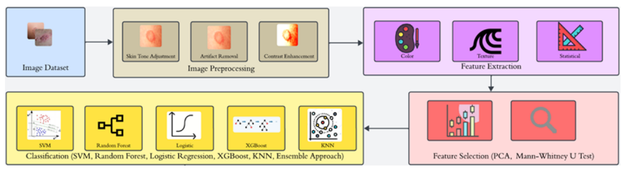


Fig. 1. Methodology for Automated Classification of Skin Fungal Infections

A. Image Preprocessing

This study involves several key preprocessing steps, essential for enhancing the quality and consistency of the input:

- Skin Tone Adjustment: The images are converted from BGR to LAB color space to separate the lightness component from color information. The mean lightness is adjusted to a target level, enhancing the overall skin tone while preserving color details. The adjusted L channel is recombined with the A and B channels and converted back to BGR color space.
- Artifact Removal: Dark artifacts such as hair are removed by converting the image to grayscale, applying morphological filtering to highlight dark regions, and using a binary threshold to identify and paint over these regions using the Telea inpainting algorithm.
- Shape Detection and Outline: Gaussian blur is applied to the grayscale image to reduce noise. The Canny edge detection algorithm identifies edges, and the contours of these edges are detected. An approximate polygonal representation of these contours is calculated to highlight regions of interest.
- Corner Detection: The Harris corner detection method identifies significant corner points. Gradients are calculated, the structure tensor elements are computed, and local sums are iterated over each pixel. The corner response function marks pixels with strong responses, highlighting potential corners.
- Image Sharpening: A sharpening filter is applied using convolution to enhance the clarity and detail of the images.
- Contrast Enhancement: The images are converted to YUV color space, and histogram equalization is applied to the luminance channel to enhance contrast. The images are then converted back to BGR color space, followed by a linear transformation to adjust contrast and brightness.

B. Feature Extraction

Feature extraction is crucial for capturing the relevant characteristics of the images. This study focuses on four types of features:

- Texture Features: The LBP method is applied to grayscale images to capture texture details. The LBP image is then flattened into a one-dimensional array.
- Color Features: The color information is extracted by analyzing the color distribution and histograms in different color spaces.
- Structural Features: The images are converted to grayscale, and the Canny edge detection algorithm is used to detect edges. The detected edges are labeled into connected regions, and properties such as area, perimeter, and eccentricity are calculated for each region.
- Statistical Features: The grayscale images are analyzed to extract statistical measures. These include mean intensity, standard deviation, skewness, and kurtosis of the pixel values, providing insights into the distribution and variability of intensities.

C. Feature Selection

Feature selection helps in reducing the dimensionality of the dataset by identifying the most informative features:

- PCA: PCA is used to reduce the dataset to 50 principal components, retaining the most significant variance in the data while simplifying the dataset.
- Statistical Tests: The Mann-Whitney U test to identify significant features between fungal and non-fungal images. Features with a p-value less than 0.05 are selected for further analysis.
- Top-n Features: The top 1000 features identified by the Mann-Whitney U test are selected based on their significance for classification.

D. Classification

Several machine learning classifiers are evaluated for their performance in classifying fungal and non-fungal skin infections:

- SVM: An SVM with an RBF kernel is used for classification.
- Random Forest: A Random Forest classifier with 100 estimators is employed to capture the complex relationships in the data.
- Logistic Regression: Logistic Regression with a maximum iteration limit of 8000 is used to model the probability of each class.
- XGBoost: XGBoost, a powerful gradient boosting algorithm, is applied for its robustness and accuracy. KNN: KNN with 5 nearest neighbors based on the proximity of data points.
- Ensemble Approaches: Three ensemble methods are evaluated:
  - Voting Classifier: Combines predictions from the 5 classifiers using soft voting to average the probabilities predicted by each classifier.
  - Bagging Classifier: Uses Decision Trees as base estimators, training multiple models on random subsets of the dataset.
  - AdaBoost Classifier: Uses a Decision Tree as the base estimator, sequentially adding models to correct the errors of previous ones.

IV. Results

In this study, we evaluated the effectiveness of different feature selection methods and machine learning classifiers for the automated classification of skin fungal infections. Fig 2 presents the preprocessing pipeline of a few sample images from the dataset. Table 1 presents statistical features extracted from a few sample images from the dataset. In this study, we evaluated the effectiveness of different feature selection methods and machine learning classifiers for the automated classification of skin fungal infections.

The classification performance was assessed using accuracy, F1 score, recall, precision, and specificity metrics.

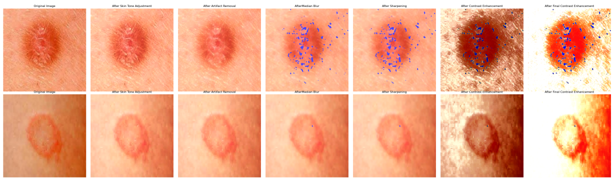


Fig. 2. Preprocessing pipeline for Automated Classification of Skin Fungal Infections

TABLE I
STATISTICAL FEATURES EXTRACTED FROM SAMPLE IMAGES

Image Name	mean	std_dev	skewness	kurtosis
124_VI-shingles	133.873	21.339	-0.446	0.720
13_VI-shingles	156.167	39.874	-0.129	-1.042
158_VI-chickenpox	129.093	38.323	-0.213	-0.633
15_VI-chickenpox	158.312	43.369	-1.096	0.193
16_FU-ringworm	166.49	22.997	-1.138	0.611
66_VI-shingles	171.586	40.199	-0.739	-0.272
75_FU-ringworm	151.246	23.256	-0.353	-1.147

The results for each feature selection method—PCA, p-test, and top-n features—along with the performance of five individual classifiers (SVM, Random Forest, Logistic Regression, XGBoost, KNN) and three ensemble methods (Voting, Bagging, Boosting) are detailed below.

A. PCA Approach

Using PCA for feature selection, the XGBoost classifier achieved the highest accuracy of 82%, followed closely by the Voting and Bagging classifiers with the same accuracy. The Random Forest classifier also performed well with an accuracy of 79%. In terms of the F1 score, XGBoost again led with a score of 81%, with Voting and Bagging classifiers showing similar performance. The precision and recall for XGBoost were 81% and 82%, respectively, indicating a strong balance between correctly identified fungal infections and non-fungal infections. Table 2 and Table 3 summarize the classification performance of various machine learning models and ensemble approaches, respectively when PCA is used for feature selection. Fig 3 depicts the confusion matrix for XGBoost classifier.

TABLE II
PERFORMANCE METRICS FOR DIFFERENT CLASSIFIERS WITH FEATURE SELECTION USING PCA

Metric	SVM	RF	LR	XGBoost	KNN
Accuracy	66.5%	78.5%	66.1%	81.5%	75.5%
F1 Score	62.3%	77.9%	64.8%	81.2%	75.3%
Recall	66.5%	78.5%	66.1%	81.5%	75.5%
Precision	65.7%	78.5%	64.8%	81.4%	75.2%

B. p-test

The p-test feature selection method yielded lower accuracy across all classifiers compared to PCA. The highest accuracy was achieved by the XGBoost classifier at 70%, followed by the KNN classifier at 75%. The Logistic Regression classifier showed moderate performance with an accuracy of 69%. The F1 score for XGBoost was 68%. Table 4 and Table 5 summarize the classification performance of various machine learning models and ensemble approaches, respectively based on features selected through statistical significance testing (p-test). Fig 4 depicts the confusion matrix for Voting classifier.

TABLE III
PERFORMANCE METRICS FOR ENSEMBLE APPROACHES WITH FEATURE SELECTION USING PCA

Metric	Voting	Bagging	Boosting
Accuracy	82%	82%	73.8%
F1 Score	81.2%	81.7%	73.8%
Recall	82%	82%	73.8%
Precision	82.5%	81.8%	73.8%

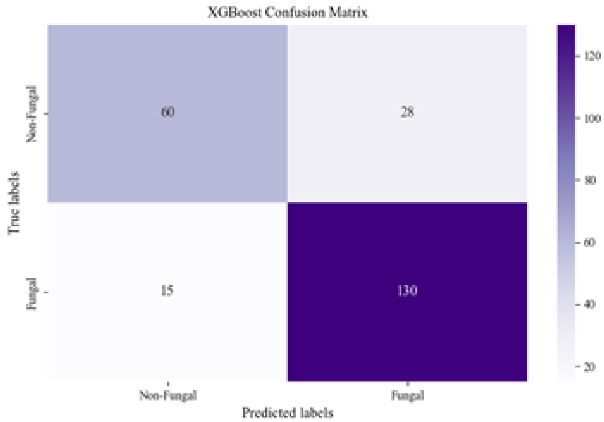


Fig. 3. Confusion matrix for the XGBoost classifier using PCA for feature selection

TABLE IV
PERFORMANCE METRICS FOR DIFFERENT CLASSIFIERS USING P-TEST-BASED FEATURE SELECTION

Metric	SVM	RF	LR	XGBoost	KNN
Accuracy	61.8%	66.1%	68.7%	70%	75.1%
F1 Score	47.5%	62%	67.9%	67.9%	74.8%
Recall	61.8%	66.1%	68.7%	70%	75.1%
Precision	38.6%	64.9%	67.8%	69.3%	74.7%

TABLE V
PERFORMANCE METRICS FOR ENSEMBLE APPROACHES USING P-TEST-BASED FEATURE SELECTION

Metric	Voting	Bagging	Boosting
Accuracy	74.2%	72.1%	60.9%
F1 Score	72.7%	69.8%	60.7%
Recall	74.2%	72.1%	60.9%
Precision	74.4%	72.45	60.5%

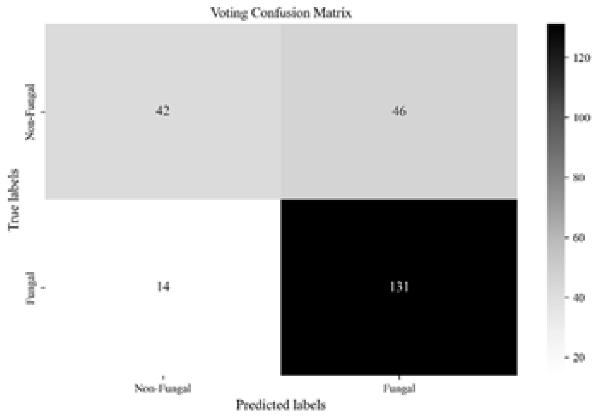
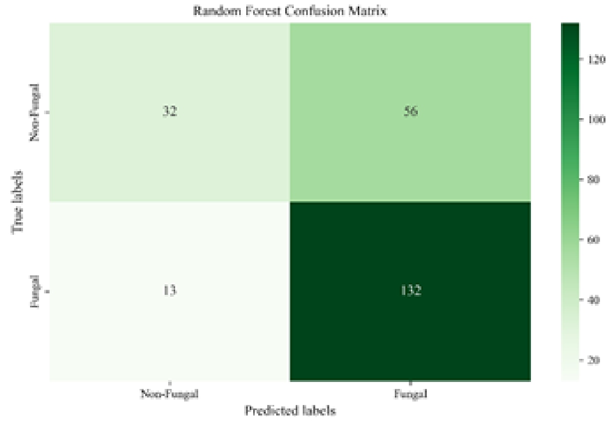


Fig. 4. Confusion matrix for the Voting classifier using p-test for feature selection



C. Top_n Approach

The top-n feature selection approach showed intermediate results between PCA and p-test. The XGBoost classifier achieved an accuracy of 73%, while the KNN classifier showed similar performance with an accuracy of 75%. Logistic Regression also performed well with an accuracy of 70%. The F1 score for XGBoost was 71%, indicating a good balance between precision and recall. Table 6 and Table 7 summarize the classification performance of various machine learning models and ensemble approaches, respectively when the top 1000 features, identified by their importance score. Fig 5 depicts the confusion matrix for Random Forest classifier.

TABLE VI
PERFORMANCE METRICS FOR DIFFERENT CLASSIFIERS USING TOP-N FEATURE SELECTION

Metric	SVM	RF	LR	XGBoost	KNN
Accuracy	62.2%	70.4%	69.5%	73%	74.7%
F1 Score	47.7%	67.5%	69.3%	71.4%	73.6%
Recall	62.2%	70.4%	69.5%	73%	74.7%
Precision	38.7%	70.6%	69.1%	72.8%	74.4%

TABLE VII
PERFORMANCE METRICS FOR ENSEMBLE APPROACHES USING P-TEST-BASED FEATURE SELECTION

Metric	Voting	Bagging	Boosting
Accuracy	71.7%	70.4%	62.2%
F1 Score	71%	68.1%	61%
Recall	71.7%	70.4%	62.2%
Precision	71%	70%	60.7%

V. CONCLUSION

XGBoost with PCA feature selection achieved the highest accuracy (82%). Ensemble methods (Voting, Bagging) also performed well, highlighting the benefits of combining classifiers. The p-test approach yielded lower accuracy, while top-n selection provided intermediate results. These findings demonstrate the effectiveness of machine learning for fungal infection classification. Ensemble methods suggest potential for even higher accuracy. Integrating these methods can empower healthcare professionals for improved diagnostics and patient outcomes. Future work should expand the dataset to include more skin conditions, refine preprocessing and feature extraction techniques, and validate the system in clinical settings. This study lays the groundwork for further research and development in machine learning for dermatological diagnostics, aiming to enhance clinical decision-making and patient care.

REFERENCES

[1] D. Seth, K. Cheldize, D. Brown, and E. E. Freeman, “Global burden of skin disease: inequities and innovations,” *Current dermatology reports*, vol. 6, pp. 204–210, 2017.

[2] P. Gupta, J. Nirmal, and N. Mehendale, “A survey on computer vision approaches for automated classification of skin diseases,” *Multimedia Tools and Applications*, pp. 1–33, 2024.

[3] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, “Dermatologist-level classification of skin cancer with deep neural networks,” *nature*, vol. 542, no. 7639, pp. 115–118, 2017.

[4] M. Ahammed, M. Al Mamun, and M. S. Uddin, “A machine learning approach for skin disease detection and classification using image segmentation,” *Healthcare Analytics*, vol. 2, p. 100122, 2022.

[5] S. Biswas, “Skin-disease-dataset,” 2023, accessed: 24-Jun-2024. [Online]. Available: https://www.kaggle.com/dsv/6695743

[6] A. Jain, M. L. Saini, A. Saklani, and A. Biju, “Tinea-corporis skin disease detection using cnn and kernel svm,” in *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)*. IEEE, 2023, pp. 157–161.

[7] V. Nimesh and R. Weerasinghe, “Differential diagnosis of ringworm and eczema using image processing and deep learning,” in *2021 21st International Conference on Advances in ICT for Emerging Regions (ICter)*. IEEE, 2021, pp. 147–152.

[8] T. D. Nigat, T. M. Sitote, B. M. Gedefaw *et al.*, “Fungal skin disease classification using the convolutional neural network,” *Journal of Healthcare Engineering*, vol. 2023, 2023.