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A Comparative Evaluation of Machine Learning based Approaches for Detection of Papulosquamous Skin Diseases

Krupali Dhawale[1], A. R. Patil Bhagat[2] and Lakshmi Madireddy[3]
[1,2]Yeshwantrao Chavan College of Engineering, Nagpur /Department of Computer Technology, Nagpur, India
Email: krupali.acem@gmail.com, arbhagatpatil@gmail.com
[3]Faculty of Engineering and Technology, Datta Meghe Institute of Higher Education & Research Wardha

***Abstract*—Papulosquamous skin diseases are challenging to diagnose due to overlapping features like erythema and scaling. Traditional Machine Learning models demonstrated moderate effectiveness but lagged in accuracy compared to Deep Learning models, which excel in processing complex dermatological images. This study highlights the value of diverse, high-quality datasets in advancing diagnostics for rare Papulosquamous skin conditions. This paper evaluates importance of ML (Machine Learning) and DL(deep learning) models used to classifying these Papulosquamous skin disorders using dermatological image datasets. Evaluation performance criteria including accuracy, precision, and recall are used to compare three Deep Learning models (ResNet50, VGG16, and InceptionV3) and six Machine Learning classifiers (SVM, LR, RF, DT, XGBoost and ANN). InceptionV3 achieved with highest accuracy (92%), followed by ResNet50 and VGG16. The results highlight the potential of DL models is improving diagnostic accuracy for rare skin diseases.**

***Index Terms*— Skin lesion, Machine Learning Approaches, Deep Learning Network, Papulosquamous skin Lesion disorders.**

I. INTRODUCTION

The etiology of Papulosquamous skin diseases is complicated, involves genetic factors, progresses slowly, and does not completely heal with treatment. . As the body's primary defense, it protects against UV radiation, heat-induced rashes, itching, lesions, dark patches, and infections. Constant exposure to environmental and internal stressors makes skin conditions highly prevalent, underscoring the importance of regular care and prevention. Comprising the dermis, lymphatic systems, underlying tissues, nerves, muscles, and blood vessels, the skin is more than just a protective barrier, it is a dynamic organ capable of adapting to changing external factors. Its outer layer defends against germs, viruses, allergens, and fungal infections, signaling issues through swelling, redness, itching, and burning. Papulosquamous disorders, a prominent group of skin conditions, require careful evaluation of tissue reaction patterns and inflammatory responses for accurate diagnosis. Skin disorders are prevalent in society, with Papulosquamous disease being a significant concern. It causes redness, skin damage, and loss, influenced by genetic and environmental factors. The main issue in diagnosing is that their symptoms frequently overlap. Skin diseases can greatly impact health, seeking care only when severe. Similar symptoms among conditions make diagnosis challenging, but early detection can prevent progression and aid recovery.

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This paper highlights four serious skin conditions: Pityriasis Rosea, Lichen Planus, Psoriasis and Pityriasis Rubra Pilaris [1],[2]. Consequently, these illnesses are frequently misdiagnosed, which can lead to medical negligence [3],[4]. As a result, a patient may experience worsening of their illness and in certain situations, even death. Conversely, with the right training, neural network algorithms able to classify these illnesses with ease [3],[5]. To obtain a thorough and reliable analysis, this study included a variety of machine learning techniques, including XGBoost, Random Forest, Support Vector Machine, Decision Tree, Random Forest, Logistic Regression, and Artificial Neural Network (ANN) classifiers [5, 6]. The detection of papulosquamous skin lesions are the primary purpose of this study. Standardized data were used as inputs for deep learning models, and then the data were classified. Performance evaluation metrics, including precision, recall, f1 score, and accuracy metrics, were used to evaluate the technique's efficacy. This study uses a small dataset of 3,620 photos to evaluate the performance of six different machine learning classifiers for identifying papulosquamous skin lesions. The pretrained CNN classifier model was used to classify the images in order to assess and compare the efficiency of these machine learning techniques. According to the comparative analysis, InceptionV3 achieves the highest classification accuracy of 92% in diagnosing the diseases. We provide a brief review of the relevant work in Section II. Section III outlines the proposed methodology, data collection and pre-processing methods utilized in this study on Papulosquamous skin diseases. Our proposed method and the corresponding experimental results are described in detail in Sections IV and V. Section VI describes the paper's conclusion.

II. LITERATURE REVIEW

Several research work applied machine learning based techniques for diagnosing Papulosquamous. A dataset of 3000 photos was examined in this study [7] in order to diagnose diseases like SJS-TEN, acne, and lichen planus. In this research work, to limit overfitting and reduce computational complexity, pooling layers decreased input size, ReLU functions added non-linearity, and convolutional layers were used for pattern recognition[7]. For training precision and error visualization, the performance of five models—Naive Bayes, SVM (Support Vector Machine), LR (Logistic Regression), CNN (Convolutional Neural Network), and Random Forest were compared using a confusion matrix. In 2024, Arshia Estkandari et al. [8] utilized a 50-layer ResNet model to diagnose psoriasis and lichen planus, achieving 89.07% accuracy, 86.46% sensitivity, and 86.02% specificity Abdullah S. Alotaibi [9], in 2022, presented a hybrid model that combined the ReliefF algorithm with KNN for identifying numerous skin illnesses, with pityriasis rosea, chronic dermatitis, psoriasis, seborrheic dermatitis, lichen planus and pityriasis rubra pilaris. In this paper the model accomplished prominent performance metrics, with an accuracy of (94.59%), recall of (90.94%), precision of (94.72%), F-score of (92.79%), and a Kappa coefficient of (93.20%).In 2022, Syeda Fatima Aijaz et al. [10] employed a CNN model combined with LSTMs to predict psoriasis, with the CNN achieving an accuracy of 84.2% and the LSTM achieved 72.3% of correctness.In 2022, Elsayad et. al. , [11] applied SVM, BO, and ECOC frameworks to diagnose six different diseases. In this study achieved training and test accuracies of (98.81%) and (99.07%), respectively. In 2024, Rastogi et al., [12] CNN model with random forest algorithm to diagnose rosacea, Actinic Keratosis, Basal Cell Carcinoma, Eczema, and Acne on the face, achieving an accuracy of 56.21%.In 2023, P. Achararit et al. [13] used the Xception model to distinguish between oral lichen planus (OLP) and non-OLP, achieving an accuracy ranging from 82% to 88%. S. Putatunda et al. [14] employed a hybrid deep learning model combining Derm2Vec with Deep Neural Networks (DNN) and an advanced DNN-Deep Neural Network framework, achieving impressive diagnostic accuracies of 96.92%, 96.65%, and 95.80% for (Erythemato Squamous Disease-ESD).Thus, the study not only sheds light on diagnosing these diseases early but also presents how new age machine learning methodologies, specifically deep learning and computer vision, can enhance precision, recall f1-score ,severity and sensitivity of skin disease classification.

III. PROPOSED METHODOLOGY

The objective of the study is to detect Papulosquamous skin Lesion disorders. The overall workflow of the analysis has been shown in Fig. (1).The whole process can be divided into 3 main phases.
1)SKIN Diseases Data Collection and Data Pre-processing 2)Data Pre-processing 3) Model Training and Testing:

- SKIN Diseases Data Collection and Data Pre-processing:In this study , 19,500 images of 23 skin diseases, sourced from DermNet (http://www.dermnet.com/), kaggle (Pattnayak et al., 2024)[15]. In this paper, we used 3120 images samples collected from Dermnet , In addition to that , this dataset is separated into two directories: the train directory has 400 photos, while the test directory contains 100. These four dataset classes Psoriasis, Pityriasis Rosea, Pityriasis Rubra Pilaris, and Lichen Planus were divided into train and test splits including clinical attitudes and Histopathological features age, gender color, texture Papules, plaques, itching, patient history, genetic factor and Symmetry. For testing and training, the ratio of 85% to 15% is taken into account.

- Data Pre-processing: Images were resized, normalized, cropped, and enhanced for consistency. Augmentation techniques like flipping, rotating, and adjusting contrast improved robustness.
- Data Augmentation: The DermNet dataset contains JPEG images with varying resolutions. Class balancing strategies, such as removing data from the majority class, address imbalance and reduce false negatives, as shown in Equation (1).

$$Dataset_N = Dataset_O - (Dataset_{Max} - Datset_{Min}) \tag{1}$$

Here, DatasetN is refer to new dataset and DatasetO is refer to old dataset.

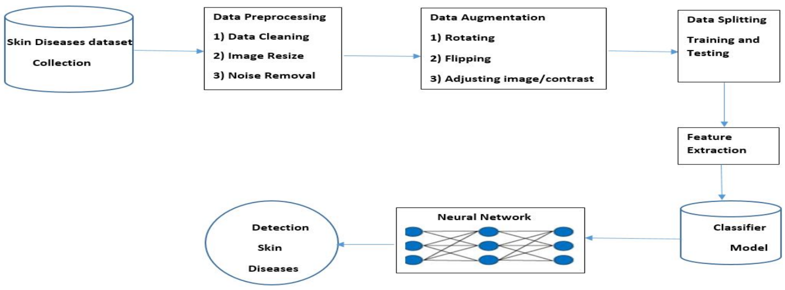

Figure 1. Proposed Architecture

- Model Training and Testing : The dataset demonstrates an imbalance, with certain classes containing approximate 3120 images, while others have approximately 300. Notably, an image is included within the dataset. To utilize this dataset effectively, it is crucial to implement strategies to balance the number of images across classes lichen planus : 197, Pituris Rosa : 98 , Pituris Rubra : 50 ,psoriasis : 650.This work uses transfer learning and the InceptionV3 model is used to classify uncommon papulosqumous skin diseases. Adam optimizer guarantees effective training, specialized layers boost task-specific learning, preprocessed datasets improve feature extraction, and categorical cross-entropy performs exceptionally well in multi class classification tasks. The models efficiency is confirmed by evaluation measures, which also demonstrate how deep learning may increase the precision of dermatological disease diagnosis.

IV. Machine Learning Classifier

The graph compares the performance of 6 machine learning classifiers (SVM, KNN, RF, XGBoost, LR, and ANN) for detecting four skin diseases: Pityriasis Rosea(PR), Lichen Planus(LP), Pityriasis Rubra Pilaris(PRP), and Psoriasis(P). XGBoost and ANN consistently show the maximum performance across all metrics with precision, recall, f1-score, and accuracy, achieving values close to 89%.

SVM, KNN, and RF also perform well, with slightly lower scores than XGBoost and ANN. Logistic Regression (LR) has noticeably lower performance, mainly in recall and f1-score, so it is least effective classifier for this task. Across all classifiers, performance is generally high, indicating that the models effectively classify the skin diseases as shown in Fig. (2). XGBoost is the top-performing classifier with the highest accuracy of 92%, consistently achieving excellent precision, recall, and F1-scores across all diseases, especially for Psoriasis. KNN follows with 92% accuracy, excelling in recall for Pityriasis Rosea. RF and ANN achieve accuracies of 90% and 89%, respectively, while SVM (85%) and Logistic Regression (63%) underperform, emphasizing the advantage of advanced models like XGBoost for skin disease classification. Equation (2) describes the test accuracy, which provides the performance value of the overall corrected diseases of the suggested work. This value is determined by dividing the whole amount of correct positive and correct negative classes by the sum of the right four classes.

$$\text{Correctly identify the diseases (\%)} = \frac{TP+TN}{TP+TN+FP+FN} * 100 \tag{2}$$

Test specificity, or it is the proportion of accurately recognized healthy individuals to estimated total number of healthy skin lesions, provides the percentage of healthy individuals who are accurately identified as healthy:

$$\text{Specificity}(\%) = \frac{TN}{TN + FP} * 100$$

The fraction of correctly forecast positive interpretations to all anticipated positives is known as precision. Another name for this is Positive Predictive Value.

$$\text{Positive Predictive Value Or Precision}(\text{P}) = \frac{TN}{TP+FP}$$

Since accuracy scores were reported in the majority of the works, this paper displayed accuracy for comparison sake in this evaluation in fig.(2).

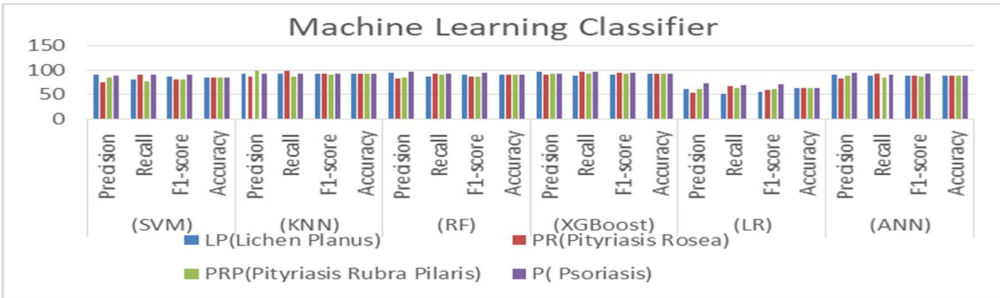

Figure 2. Comparative Evaluation of Machine Learning

V. Result Analysis with Deep Learning Models

Pretrained models like Residual Network 50(ResNet50), Visual Geometry Group 16(VGG16), and InceptionV3 are widely used for medical image classification tasks, including skin disease detection, due to their advanced architectures and transfer learning capabilities.

ResNet50 or Residual Network 50: This deep convolutional neural network tackles the vanishing gradient issue with residual connections, enabling seamless training across 50 layers. It enhances accuracy in tasks like image classification, effectively differentiating skin conditions such as Pityriasis Rubra, Pityriasis Rosea, Lichen Planus, and Psoriasis, as represented in Equation (3).

$$Output = \frac{e^{z_i}}{\sum_{j=1}^{4} e^{z_i}}, i \text{ €}\{\text{psoriasis, lp, pr, and PRP}\} \quad (3)$$

VGG16, or Visual Geometry Group 16: It is a 16-layer deep neural network with three fully connected layers follows 13 convolutional layers. It has been pre-trained on ImageNet for feature extraction, employs 3x3 receptive fields, and uses max-pooling to reduce dimensionality. In order to assess the effectiveness of the VGG16 skin disease classification model, the loss of cross-entropy function is shown in Equation [4].

$$Loss\ function = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{4} y_{ij} \log(Probabilty_{ij}) \quad (4)$$

Such as: N describe the number of samples for Papulosquamous skin diseases, with genetic factors, progresses slowly, and does not completely heal with treatment.

yij is the true label for class j of sample i .

$Probability_{ij}$ - For sample i , it is the detected probability for class j

Inception V3: The InceptionV3 model used transfer learning to accurately classify four skin diseases: Papulosquamous skin diseases (Lichen Planus, Pityriasis Rosea, Pityriasis Rubra Pilaris, and Psoriasis.) By resizing and normalizing images to 299x299, the model benefits from pretrained knowledge, which is fine-tuned with additional custom layers for disease classification. After training for 19 epochs, the model delivers high 92% accuracy shown in Figure[2]. To assess performance, a confusion matrix is employed, demonstrating the model's capacity to differentiate between the illnesses. This method highlights the power of InceptionV3 in enhancing skin disease detection to avid the muscles biopsies. This makes it efficient and accurate for categorizing conditions like Pityriasis Rubra, Pityriasis Rosea, Lichen Planus, and Psoriasis. In order to detect Papulosquamous skin illnesses, the model uses Equation (5) to calculate the likelihood of each class and choose the one with the highest probability.For given input image y, the predicated probability for specific class I where i={ psoriasis, lp, pr, and PRP }

$$Probability(Diseases|y) = \frac{e^{z_i}}{\sum_{j=1}^{4} e^{z_i}}, i \text{ €}\{psoriasis, lp, pr, and\ PRP\} \quad (5)$$

Where Zi: The raw logit score for class four is the output generated by the last fully connected layer of the Inception V3 model before applying the softmax function.

Probability (Disease|y): The Probability of class i given the input image y.

$\sum_{j=1}^{4} e^{z_i}$: Sum of exponentials of the logits across all four classes to normalize the probabilities.

The evaluation of the classification model yielded the following performance indicators for each class: The precision values, which show the proportion of anticipated positive cases that are correctly detected, are 0.923, 1.0, and 0.75 for the respective classes. These classes respective recall metrics of 0.923, 0.846, and 1.0 demonstrate the accuracy with which all real positive cases can be identified.

Figure 3. Accuracy Result of Algorithm

Finally, for a more thorough performance review, the F1-scores, which balance precision and recall, are 0.923, 0.917, and 0.857.

VI. Conclusions

This study compared six machine learning models (SVM, LR, RF, DT, XGBoost, and ANN) with deep learning models (ResNet50, VGG16, and InceptionV3) for detecting Papulosquamous skin diseases. InceptionV3 achieved the highest accuracy at 92%, followed by ResNet50 and VGG16. While XGBoost and ANN performed well, deep learning models outperformed traditional methods. In future, we will integrating models like Vision Transformer (ViT) and YOLO could further improve detection accuracy and speed, highlighting the potential of advanced deep learning techniques for efficient skin disease diagnosis.

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