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Facial Skin Disease Detection

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Abstract— Facial skin problems encompass a range of conditions, including acne, rosacea, eczema, psoriasis, dry skin, wrinkles, hyperpigmentation, allergic reactions, and skin cancer. These issues can result from various factors such as genetics, environment, and lifestyle. Proper skincare, avoiding triggers, and seeking medical advice when needed are essential for managing such problems. A dermatologist can help diagnose the specific condition and recommend personalized treatment options for optimal skin health. Inception v3, a deep learning model designed for image recognition, is considered for detecting facial skin diseases due to its ability to recognize complex features, support transfer learning, deep architecture for hierarchical feature representation, strong community support, and demonstrated state of-the-art performance in image classification tasks. With an accuracy of 89.24%, its versatility makes it suitable for adapting to the specific task of facial skin problem detection. However, the choice of the model depends on factors such as the dataset, problem nature, and computational resources. It should be part of a comprehensive system involving clinical validation and collaboration with healthcare professionals for accurate diagnosis and treatment.

Index Terms— convolutional neural network(CNN) , deep learning , facial Skin disease, Inception V3.

I. INTRODUCTION

The skin, which is the largest organ in the body, provides crucial functions such as protection from external elements, sensation, temperature regulation, immune defense, and synthesis of vitamin D. Comprising three main layers — epidermis, dermis, and subcutis — and housing various appendages, the skin requires proper care for optimal health. Regular hygiene, protection from UV rays, hydration, and a balanced diet contribute to maintaining skin well-being. Skin conditions vary, from common issues like acne to more serious diseases, underscoring the importance of both skincare practices and medical attention when needed. The face, an emblem of identity and expression, serves as the primary canvas where the subtleties and complexities of various skin diseases manifest. Amidst the intricate landscape of dermatological ailments, the detection and accurate diagnosis of facial skin diseases pose a significant challenge, requiring a blend of clinical expertise, technological advancements, and innovative approaches.

[1]A variety of ailments are included in the category

of facial skin issues, such as rosacea, eczema, psoriasis, hyperpigmentation, allergic responses, skin cancer, etc. Numerous variables, including genetics, environment, and lifestyle, might contribute to these problems. Managing face skin issues requires proper skincare, avoiding triggers, and getting medical help when necessary. The increasing prevalence of facial skin diseases is influenced by several factors. Environmental pollution, UV radiation, stress, and poor skincare practices contribute to issues. Harsh chemicals in cosmetics, poor diet, hormonal changes, and inadequate skincare routines are additional factors. Microbial infections, allergens, and occupational hazards also impact facial skin health. Genetic predisposition and climate changes play a role. Globalization and urbanization contribute to environmental exposures. Addressing this trend requires a comprehensive approach, including proper skincare, awareness of environmental factors, stress management, and seeking medical advice when necessary.

[2] It is essential for both individual and public health to identify facial skin problems at an early stage. It enables

timely intervention, prevents the spread of contagious diseases, improves the quality of life for affected individuals, and reduces the risk of complications. Regular skin screenings and consultations with healthcare professionals

can contribute to maintaining skin health and overall wellbeing. The primary objective of this research is to develop, assemble, and evaluate a deep learning model for the detection of facial skin problems using the Inceptionv3 architecture. The objective is to automatically classify and detect different skin problems based on facial photos by utilizing the capabilities of Inception-v3, a potent convolutional neural network (CNN). Here we have considered a dataset with 10 classes which are Acne and Rosacea, Atopic dermatitis(eczema), Herpes HPV, Lupus, Psoriasis, Seborrheic keratoses, Tinea ringworm, Warts Molluscum, Basal cell carcinoma and Actinic keratosis.

II. RELATED WORKS

[3] Here, the goal was to use the textural features in digital facial skin photographs to construct a model for the detection of skin diseases on the face. Textural information is extracted using a combination of the K Nearest Neighbor classification algorithm and the Gray Level Co-Occurrence Matrices (GLCM) approach. 150 digital photos of troublesome faces, split into 70% training and 30% test categories, made up the facial image data. The model accuracy produced by this study is 80%. [4] A hybrid strategy is used in this work to build “Cureto,” a smartphone-based expert system. The intended work is created, put into practice, and tested in order to

categorize skin sensitivity, acne density, and the distinct acne subtypes—pustules, whiteheads, cysts, papules, blackheads, and nodules—that are present. According to the data, 90% of the Acne types may be classified accurately. [5] In this work, they have attempted to create a neural network prototype for the detection of skin illnesses. Dermatitis hand,statis dermatitis, lichen simplex, eczema subcutes and ulcers are some of the common skin conditions that they have classes for. This study is a hybrid of machine learning and photo handling techniques. There are five skin classes included in the preparatory information. Their accuracy rate is 73%. [6] They have presented a prototype in this study that allows them to quickly and affordably identify the issue. This was primarily an image processing method. Based on some feature extraction, our suggested system can identify multiple types of skin diseases using color segmentation technique with SVM classifier. Their approach effectively detects eight distinct skin conditions, with a 94.79% accuracy rate. [7] This study compiles a large number of prior research articles on machine learning-based approaches for classifying skin disorders. According to the survey, there was a noticeable variation in the diagnostic accuracy of image processing techniques, with results ranging from 50% to 100%. Regarding the tissue feature treatment techniques, the accuracy was at least 94%, which is considered outstanding.

[8] This study proposes a medical AI framework based on data width evolution and self-learning to deliver medical services for skin disorders that meet the needs of individualization, extendibility, and real-time. Three types of deep learning models are loaded and compared: VGG16, LeNet-5 and AlexNet. The ultimate accuracy rate came to 78%. [9] The proposed method uses a deep CNN ResNet152 and an InceptionResNet- V2 model to first learn how to embed input images into Euclidean space. Secondly, to find distinguishing features of skin disease photos, computed the L-2 distance between matching images in Euclidean space using the triplet loss function. There was 87.42% accuracy. [10] Here, the Dermatology database was the main emphasis. The challenge was identifying the specific type of erythemato squamous disease, such as chronic dermatitis, pityriasis rosea, lichen planus, psoriasis, and pityriasis rubra pilaris. In dermatology, the differential diagnosis of erythemato squamous diseases is a real problem. Each pattern consisted of 33 numbers, one of which was nominal, and which were all inside the linear value range. 20% of the dataset being held back for approval, with the remaining 80% being used for demonstration. 85.57% accuracy was achieved. [11] The experiments make use of the DermNet NZ photo collection of face acne. Three different picture segmentation methods—Texture Analysis, K-Means and Segmentation Using the HSV Model—were applied to extract the acne region from skin photographs. The output images from K-Means and HSV are mixed with the dataset. On that dataset, one SVM model using Scikitlearn and two CNN models, one with the ReLU activation function and the other with the LeakyReLU activation function, were trained. The proposed CNN (LeakyReLU) model had an accuracy rate of 97.54%.

III. METHODOLOGY

The challenge of facial skin disease detection is recognizing and categorizing different skin conditions from pictures of the human face. This is a critical task with significant implications for healthcare, as early and accurate detection of skin diseases can lead to timely medical intervention and improved patient outcomes. Here we are detecting diseases like Acne, Rosacea, Atopic dermatitis(eczema), Herpes HPV, Lupus, Psoriasis, Seborrheic keratoses, Tinea ringworm, Warts Molluscum, Basal cell carcinoma and Actinic keratosis (Fig 1).

A. Data Collection

In order to obtain relevant and meaningful information, data collection is the systematic process of gathering and evaluating data from many sources. Here many publicly available datasets were used; Dataset named 20 Skin Diseases consist of 2492 images with a resolution of 720 x 472 and in that 556 images were assigned for testing and 1936 images were assigned for training. Dermnet consist of 3508 images, 1444 images were assigned for testing and 2064 images for training. (Fig 2)

B. Pre-Processing

Data preparation, which includes arranging, cleansing, and converting unprocessed data into a format that can be analyzed, is a crucial phase in the data analysis process. Firstly, the images were resized with 720 x 470 as resolution followed by normalizing the images. We obtained the pre-processed images which were of the resolution 720 x 470. After the pre-processing steps, the images were ready to be used as input for training and testing.

C. Training and Testing

Training set: A portion of the dataset which is 70% were used for training the model.
Testing set: The other portion which is the rest 30% were used for testing the model.

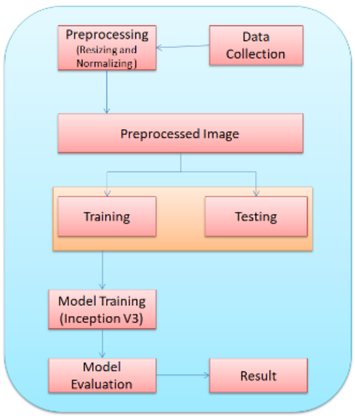

Fig 1. Flow chart

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D. Model Creation

Architecture Selection: In the proposed system, Inception V3 model was used; a deep learning model, which is the best for image classification.

Loss Function and Optimization: The loss function of the proposed system is categorical cross entropy, which quantifies the difference amongst the actual labels and the expected outputs. The optimizer used was Adam.

Hyper-parameter tuning: The hyper-parameters were adjusted for batch size 32 in order to optimize the model's performance.

Fig 2. Dataset

E. Model Evaluation

Testing the model: The trained model was given images from the testing set, and its performance was assessed by comparing the anticipated outputs with the actual labels.

Metrics: Performance indicators including as F1 score, precision, accuracy, and recall were calculated to assess the effectiveness of the model. (Fig 4)

Accuracy: accuracy provides a broad picture of accurate forecasts.

Precision: The goal of precision is to reduce false positives.

Recall: Recall seeks to record every pertinent incident while reducing false negatives.

F1 Score: Recall and precision are balanced in the F1 score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-}score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Confusion Matrix: When there is an imbalance in the distribution of classes or distinct misclassification costs for false positives and false negatives, the confusion matrix can be a useful tool for analyzing the advantages and disadvantages of a classification model. (Fig 3)

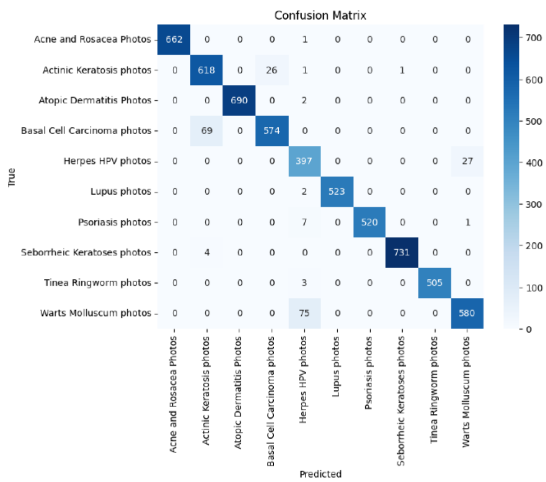

Fig 3. Confusion matrix

IV. RESULT ANALYSIS

In our comparative analysis of three studies focused on facial skin disease detection, we observe distinct trends in model performance and methodologies. Using a Convolutional Neural Network (CNN), Derm-NN was able to obtain a respectable 73% accuracy rate on a dataset of 500 photos that showed different types of skin conditions. The next investigation showed an increase in accuracy to 80% using textural feature extraction on 150 digital photos with a 70-30 training-test split. This indicates how well textural features can be used to improve classification results. Interestingly, our study presents a more sophisticated method by using the Inception V3 model to categorize ten groups of facial skin diseases (Fig 5). The outcomes show an impressive accuracy of 89.24% (Fig 4), surpassing the two earlier investigations. This highlights how important it is to use complex neural network architectures on bigger and more varied datasets so that the model can automatically pick up pertinent information for better face skin disease diagnosis. The comparative research highlights how feature extraction methods, dataset size, and model selection affect the overall robustness and accuracy of facial skin disease classification models.

Metrics	Score
Accuracy	89.24
Weighted Precision	89.83
Weighted Recall	89.24
Weighted F1 Score	89.22

Fig 4. Table of Evaluation Metrics

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V. CONCLUSION

In conclusion, our comparative study of three researches on the detection of facial skin diseases concludes with a progression in model performance and methodology. The model we developed the Inception V3 model, which successfully classified ten face skin diseases with an impressive 89.24% accuracy rate. This highlights how sophisticated neural network architectures may be used to automatically learn features and increase accuracy on bigger and more varied datasets. The comparative study emphasizes how feature extraction methods, dataset size, and model sophistication influence how well face skin disease detection algorithms work. These findings support the continuous search for more reliable and accurate methods for the early detection and diagnosis of facial skin problems as the field develops.

Fig 5. Detected labels

VI. FUTURE SCOPE

The future scope for facial skin disease detection research lies in the continued evolution of deep learning architectures, the expansion and diversification of datasets, the integration of multi-modal information, and the validation and deployment of models in real-world clinical settings. By addressing these issues, the discipline will advance and trustworthy and useful tools for the early diagnosis and identification of facial skin problems will be developed, which will ultimately benefit patients and doctors.

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