iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** VI **Month of publication:** June 2025

DOI: https://doi.org/10.22214/ijraset.2025.72462

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com

Epiderma Shield: CNN-Based Classification of Skin Diseases

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Abstract: Skin diseases are a medical condition that affects the skin. The cause of these diseases might be a virus, infection, bacteria, allergy, etc. These diseases cause itchiness, rashes, inflammation, or skin changes. To recognize and differentiate these skin conditions, we have some traditional methods like blood testing and skin scraping and some modern technology too, like lasers and microscopes, but the problem is either they are less accurate or very expensive. To overcome these, we can introduce AI in the health sector, which makes tasks very easy and cheap. The introduction of a deep learning model integrated with image preprocessing in computer vision provides remote access ith the ability to detect various skin-related diseases at early stages.
Keywords: Skin Disease Detection, Convolutional Neural Network, Deep Learning, Image Preprocessing, Alopecia, Herpes HPV, STD Classification.

I. INTRODUCTION

Skin disease is one of the widespread and common diseases especially for the people who live in tropical and subtropical regions. It is due to high temperature, humidity, and scorching heat. Generally, it is observed that people have a negligent attitude towards this type of disease, particularly in the case of men. This negligence results in developing life-threatening diseases like skin cancer. In contrast to India, which lies in a subtropical region, the people have many types of myths about skin-related diseases like chickenpox, smallpox, etc. The facilities and knowledge towards it are also very low, which demanded a root-level awareness campaign, especially in the rural areas. The shortage of dermatologists is also very high. All of these problems can be overcome by technological advancement in the health sector[1].

Our proposed model is one of the steps towards this, that detecting skin diseases only by simple uploading of an affected image. Even a common man can be capable of diagnosing his/her disease. In this model we basically detected two types of diseases: “alopecia and other hair diseases” & “herpes, HPV, and other STDs”. “Alopecia and other hair diseases” is caused by aging, heredity, and changes in hormones [2].. The “Herpes, HPV, and other STDs” are caused by bacteria, viruses, and parasites [3]. The public may benefit greatly from the study's suggestion that a Convolutional Neural Network (CNN) algorithm be used to distinguish between different disorders. Two categories of processed images were included in the dataset: one for "Alopecia and other hair diseases," and another for "Herpes, HPV, and other STDs." About 80% of these photos were set aside for training, while the remaining percentage was set aside for validation and testing. Images linked to both disease categories were intended to be recognized and segmented by the model.

II. LITERATURE SURVEY

In [4], a novel technique is introduced to recognize skin-related problems. In this technique, computer vision is used to enhance image visibility by removing artifacts, reducing variability in lighting conditions, etc., and a machine learning model is used to train the dataset of skin-related diseases. The ML is assigned to recognize skin diseases, and computer vision is assigned to fetch clear images. The model is used to test the data of six skin disease and gives the accuracy of 95%.

In [5], Kritika Sujay Rao and her colleagues studied the use of machine learning techniques for skin disease detection in the field of medical image analysis. Convolutional Neural Networks (CNNs), a deep learning method well-known for its proficiency with image-related tasks, were the main focus of their research. The importance of validation data in improving the system's accuracy was also emphasized in the study, underscoring the need for high-quality datasets to produce accurate skin disease classification results.

In [6], a model was introduced that recognizes eczema and tells its severity on its own. The model recognizes eczema in 3 levels, The first level of the model shows skin detection by segmentation technique, the second level of the model produces borders and features, namely color, and the third level of the model shows the severity of eczema through support vector machine.

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Volume 13 Issue VI June 2025- Available at www.ijraset.com

In [7], Analysis and recognition of images by using a novel software model obtained from ELM. The binary mask of skin lesion is obtained by using segmentation algorithms integrated with fusion methods. Shape and radiometric features are the fundamentals for the calculations on malignancy of lesion. For better results it is important to give some attention to the global and local parameters. The malignant melanoma can be detected in the early stages by the model.

In [8], Skin cancer images are connected by Kumar and Singh in various varieties of neural network in deep learning. Matlab is used for testing and training of a group of skin cancer images. The support of matlab is very necessary for the classification of skin cancer. A lot of research and development and application has been used in the field of medical imaging and diagnosis.

In [9], The efficiency of Convolutional Neural Networks (CNNs) for agricultural applications, particularly for the classification of diseases in potato plants using transfer learning techniques, was examined in a July 2022 study by Amit R.S. and associates. The researchers discovered that transfer learning models provided high accuracy along with a simplified implementation process. Their results demonstrated CNNs' adaptability and potential for use in domains other than traditional image classification, such as plant pathology and more general agricultural settings.

III. METHODOLOGY

The study's aim was to develop a Convolutional Neural Network (CNN)-based model for the classification and detection of two different categories of skin conditions: one that includes alopecia and other hair-related disorders, and the other that includes herpes, HPV, and other sexually transmitted diseases (STDs).

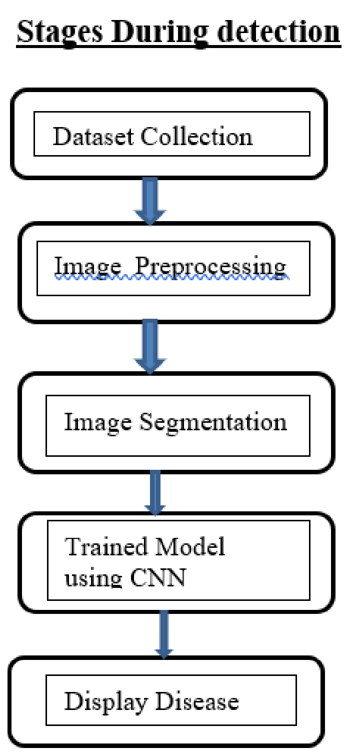

Fig. 1. Stages during detection

A. Data Collection

We have collected the sample dataset of two skin-related diseases. We have taken the dataset for “Alopecia and other hair diseases” & “Herpes, HPV, and other STDs” from Kaggle under the name “Dermnet” by Shubham Goel [10].

The dataset uses 239 images of “Alopecia and other hair diseases” & 406 images of “Herpes, HPV, and other STDs.” We have taken 52 images for the training phase, 6 images for the validation phase, and 7 images for the testing phase.

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B. Pre-processing

We've a total dataset of 644 skin images. These images are distributed into 10 batches so that they can be fluently preprocessed. The image size is set to 256 pixels. Two distinct rates — 80 20 and 70 30 — were used in the study to divide the datasets for each class into training and testing subsets. The Convolutional Neural Network(CNN) model was also trained and assessed using these divisions, allowing for a comparison to ascertain which rate produced the stylish bracket delicacy.

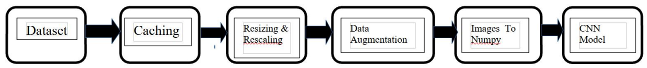

Fig. 2. CNN-Based Image Classification Workflow

The dataset was saved to the cache because it provides faster data access and helps in disk I/O reduction. This cached data is sent for further processing through the pipeline in AUTOTUNE mode. Then, data was resized in 256 x 256 format with rescaling of 1.0/255. These images are sent for the data augmentation of horizontal and vertical scaling of 0.2 radians (11.5 degrees). Now the image is converted to the NumPy that is read by the system with the help of the OpenCV Library, and then it is ready to be trained under the CNN model.

C. Segmentation

In the field of image segmentation, the system under discussion is regarded as cutting edge. It uses three- dimensional image data, with height, range, and channel count as the corresponding confines. The image resolution is defined by the first two confines, and the number of color channels which generally correspond to the red, green, and blue (RGB) intensity situations is indicated by the third dimension. Images are constantly resized before being fed into a neural network in order to maximize computational effectiveness and avoid underfitting.

For case, when a $224 \times 224 \times 3$ image is smoothed, a one- dimensional input vector of size 150,528 is produced. Such a vector still requires a large quantum of processing power indeed after the dimensional reduction, which emphasizes the necessity of effective preprocessing previous to feeding data into the network[11].

D. CNN Model

It has been discovered that convolutional neural networks(CNNs) perform better than other neural network types when recycling input like voice, audio, or images[12]. Convolutional, pooling, and completely connected(FC) layers are the three main types of layers set up in these networks. The convolutional subcaste is the primary computational element among them, handling the maturity of the processing. It uses point charts, pollutants, and input data to serve. By lowering the number of parameters, pooling layers also known as down- slice layers — help in lowering the dimensionality of the data. Pooling applies a sludge across the input, much like convolutional layers do, but these pollutants are light. Generally speaking, there are two types of pooling ways maximum pooling and average pooling.

The completely connected subcaste converts the uprooted features into final affair prognostications grounded on the input image's pixel values by connecting every neuron in one subcaste to every other subcaste's neuron.

1) *Convolutional Layer:* This model contains 5 convolutional layers that contain 32 sublayers in the first and 64 layers in the rest. Each layer is in a grid of 3x3. After passing to this layer, it sends for the pooling.
2) Max-Pooling Layer: There are 5 max-pooling layers implemented in the model. The purpose of this layer is to apply a downsampling feature to the output received from the immediate convolutional layer. For each 2D region input feature, typically a 2X2 window is implemented.
3) *Fully Connected layers:* The last layer of a convolutional neural network (CNN) usually consists of a fully connected layer that has been created by connecting all of the neurons that came before it. By combining features acquired in previous layers, this layer, which resembles a conventional artificial neural network, reduces spatial information. It is made up of several neurons that produce the final classification or prediction, beginning with input neurons and ending with output neurons.

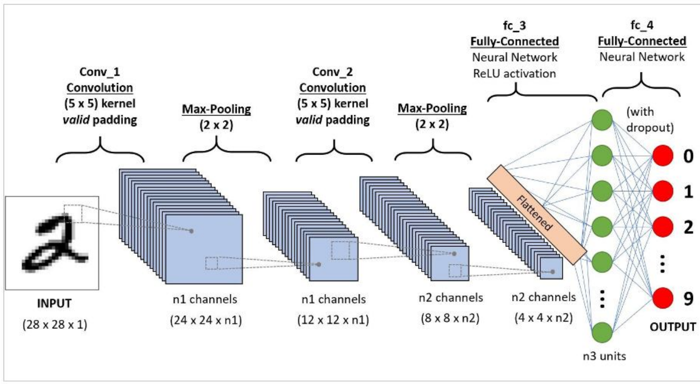

Fig. 3. *A CNN sequence to classify handwritten digits[13]*

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_3 (Sequential)   (10, 256, 256, 3)         0

 sequential_4 (Sequential)   (10, 256, 256, 3)         0

 conv2d_6 (Conv2D)           (10, 254, 254, 32)        896

 max_pooling2d_6 (MaxPoolin  (10, 127, 127, 32)        0
 g2D)

 conv2d_7 (Conv2D)           (10, 125, 125, 64)        18496

 max_pooling2d_7 (MaxPoolin  (10, 62, 62, 64)          0
 g2D)

 conv2d_8 (Conv2D)           (10, 60, 60, 64)          36928

 max_pooling2d_8 (MaxPoolin  (10, 30, 30, 64)          0
 g2D)

 conv2d_9 (Conv2D)           (10, 28, 28, 64)          36928

...
Total params: 183682 (717.51 KB)
Trainable params: 183682 (717.51 KB)
Non-trainable params: 0 (0.00 Byte)
```

Fig. 4. Layer-wise Architecture of the CNN Model

IV. RESULTS AND ANALYSIS

In our project we successfully detected a couple of skin diseases with excellent testing accuracy. The confidence is also very remarkable; images show more than 99.5 % or even 100% accuracy , which shows the reliability of our proposed paper. Now this model can work as a foundation for future skin disease-related works that help in achieving our objective of a paper to provide an easy, accurate, and quick method for detecting the diseases.

The performance and validation of the proposed CNN techniques were evaluated in a dataset, where the approach outperformed other existing methods. By critically implementing the 5 convolutional and 5 max pooling layers and 50 epochs.

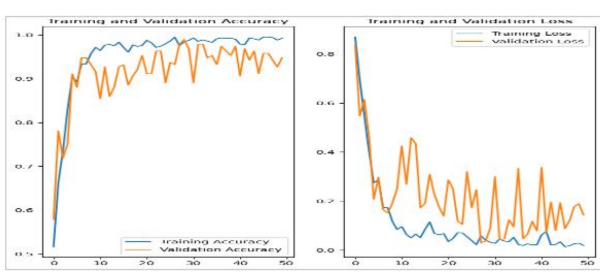

Fig. 5. Training and validation accuracy and loss

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Initially, epochs was 50 for the models. At the initial iterations, accuracy varied between 50% and 70% and gradually increased and remained around 98.6%. The overall score was 98.44%. Whereas when it observed the accuracy of validation, it showed identically to training accuracy varied from 57% to 99.5%. The overall validation score is 96.67%. When we critically observed the training loss and validation initially, it showed a high number of losses of 15%. But as epochs move further, the losses reduce gradually and come to 3.74% only, which shows the accuracy and precision of our model.

Fig. 6 Model prediction with confidence scores

Along with evaluating the CNN model's classification accuracy, the model's certainty in classifying input images was evaluated by examining the confidence scores linked to its predictions. After 50 epochs of training on a normalized and augmented dataset, the model's test accuracy of 98.44% showed that it could successfully generalize to new data. The model continuously generated high confidence scores in addition to high classification accuracy, indicating a high degree of dependability in its predictive abilities.

V. PERFORMANCE COMPARISON

TABLE I
PERFORMANCE COMPARISON WITH OTHER MODELS

Reference	Model	Accuracy
Aditi & Kaur (2021) [14]	SVM	95.99%
Gaikwad & Musande (2023) [15]	CNN	96%
Bangal et al. (2022) [16]	CNN	91.41%
Proposed Model	CNN	98.44%

VI. FUTURE WORK

Future research can look in a number of directions to increase the efficacy and practicality of CNN-based systems for skin disease detection. To improve diagnostic reach, one promising approach is to broaden the model's classification capabilities by incorporating a greater range of skin conditions, especially uncommon and underrepresented diseases. More individualized and precise diagnostic results may be made possible by including patient-specific metadata, such as age, gender, and medical history.

Adopting sophisticated pretrained models and contemporary transfer learning techniques, like transformer-based architectures or EfficientNet, may improve performance, particularly in situations where data availability is constrained[17]. Furthermore, the incorporation of Grad-CAM and other explainable AI (XAI) techniques can offer visual insights into model predictions, improving their interpretability and reliability for clinical practitioners.

In order to facilitate real-time diagnosis, especially in remote or underdeveloped areas, lightweight models that can be deployed on mobile devices must be developed. The model's dependability, usefulness, and continuous development will also depend on involving dermatologists in feedback loops and carrying out real-world clinical validation through trials.

VII. CONCLUSION

Convolutional Neural Networks (CNNs) were used in the study's deep learning-based model to identify two types of skin diseases, designated A and B. With a testing accuracy of 98.44%, the researchers came to the conclusion that CNN was the best method for this classification task. According to the suggestion, the healthcare industry could be significantly impacted by such a system, especially since it would allow patients to receive quick disease detection with little effort[18]. The authors also pointed out that early diagnosis and treatment are still difficult in rural areas of India, where literacy rates are relatively low . They thought that in these underprivileged areas, this model might help with better early skin disease detection and treatment[19].

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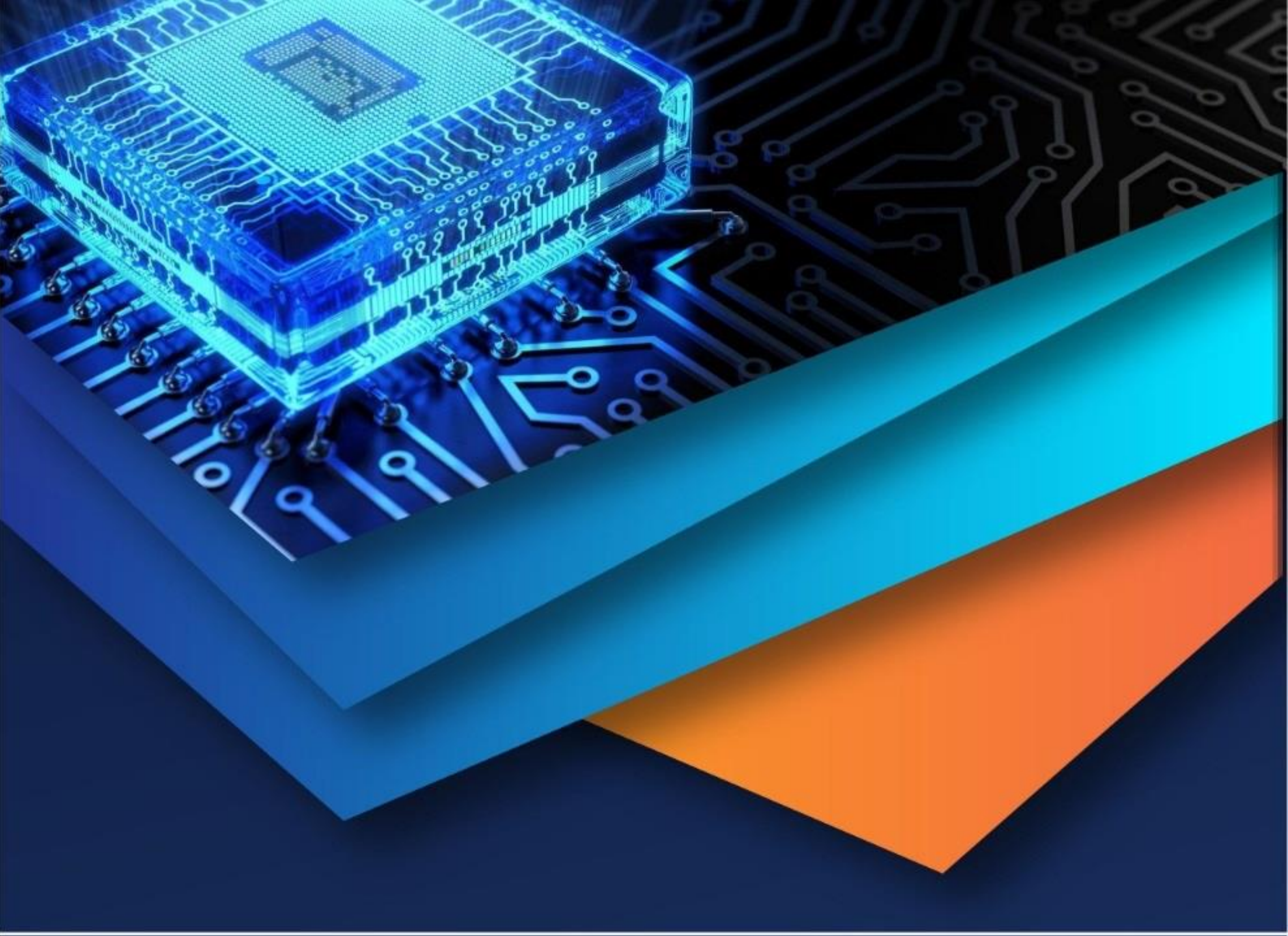

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