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Instant Skin Disease Prediction Bot

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ABSTRACT: Skin disease detection using deep learning is a cutting-edge approach aimed at automating the process of identifying and diagnosing various skin conditions. These networks learn complex patterns and features directly from the images, enabling them to accurately classify different skin diseases. This abstract explores the application of deep learning in skin disease detection, highlighting its potential to revolutionize dermatological diagnosis by providing rapid, accurate, and scalable solutions. Additionally, it discusses challenges such as dataset diversity, model interpretability, and clinical integration, along with potential future directions for research and development in this rapidly evolving field.

KEYWORDS: Skin disease detection, Deep learning, Convolutional neural networks (CNNs), Data Augmentation, Image classification, Positional Bias

I. INTRODUCTION

In the age of increasing health problems, many health problems cannot be ignored; "skin diseases", the effects of which will last longer and will be easier. The body is affected by almost all known and unknown air diseases and causes many etiological problems. Most don't know. Therefore, most texts today focus on location (e.g. mucosal conditions), morphology (blistering pain), cause (skin pain caused by physical factors), etc. It is divided accordingly. Approximately 2 square meters (22 square feet), there are three layers: epidermis, dermis and subcutaneous tissue. and hair follicles Epidermis is the uppermost squamous epithelium of the skin and consists of several layers: stratum corneum, stratum lucidum, stratum granulosum, stratum spongiosa and stratum basale. Since the epidermis does not have a direct blood supply, nutrients are transferred to this process from the dermis. There are four types of cells in the epidermis: keratinocytes, melanocytes, Langerhans cells and Merkel cells; their main components are keratinocytes and constitute approximately 95% of the epidermis. The dermis is the layer of skin between the epidermis and the subcutaneous tissue and consists of the two papillary dermis and reticular dermis. The main source of tissue is adipocytes or adipocytes. Tissues can be divided into two parts, the fat layer or lipid membrane and the inner layer of the muscle (lipid membrane). The main source of tissue is adipocytes or adipocytes. Tissues can be divided into two parts; the fat layer or lipid membrane and the inner layer of the muscle (lipid membrane). It is often associated with foot infections and fungal infections, excessive sweating, and sharing towels or gym clothes. Melanoma is the most dangerous type of cancer. It is produced by melanin-producing cells called melanocytes. It usually appears on the skin, but rarely in the mouth, intestines, or eyes (uveal melanoma). In women, melanoma often occurs on the legs; Melanoma is often called malignant melanoma. However, the medical community says there is no such thing as "benign melanoma" and recommends avoiding the term "malignant melanoma" because it is not possible. Approximately 25% of melanomas develop from moles. Changes in a mole that may indicate melanoma include growth (especially rapid growth), irregular edges, colour changes, itching, or cracks in the skin. Few skin diseases are very similar but there are aspects to that disease which when found out with their minute details can be separated into two different diseases one such type of example is Melanoma and Melanocytic Nevi. Melanoma doesn’t have a crested layer above it whereas melanocytic nevi does have a crested layer which lifts the skin on the patch with a dried layer. These are some examples that signify the importance of finding or extracting minute details which are the backbone for differentiating two classes. The first part of this article briefly describes some existing studies and visual clues that doctors use for dermatological diagnosis. Part II is devoted to the

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introduction of the plan. All tests performed and performance evaluation results of the method are presented. The last section presents a discussion and conclusion.

II. RELATED WORK

The most common approach found among most of the research papers and the existing system is the usage of segmentation through multiple forms of the U-Net architecture [8] also Different models have been put into use for training purposes to increase the efficient as one system used Mobile Net V3 [9] and other systems used Efficient Net [5] ,Convent-ST-AFF [2] along with gaussian mixture models .it was also observed that these images with diseases investigation using GMM based modelling of GLCM parameters showed that different types of dermatologists disease have unique peak structure can easily predicted by using their colored images[1].Customized form of resnet's were being used which are the product of collective combinations of multiple models which compared to current mainstream medical image segmentation had significant improvements in all test values and is suitable for medical imaging[8].Traditional Data Augmentation is used to introduce geometric transformations on the existing data with rotate and clipping as their properties [3].Semantic segmentation has been extensively used as the foundational image processing technique for better understanding of patterns of different skin conditions [4].Many research works aims to provide implementable solutions at the applications side through which this work was made to be available such as through, IOT led remote skin disease diagnosis application which can be achieved more efficiently with advanced IOT technologies which makes use IOT data processing and learning algorithms [6]

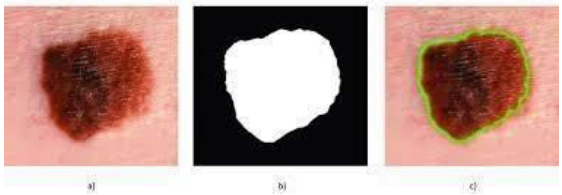

Fig 1: Semantic Segmentation

III. PROPOSED SYSTEMS

The presence of data augmentation in the existing system uses two properties which are rotation and clipping, using only two properties of data augmentation limits the extensive potential of augmenting the data which may not reduce positional bias to a considerable level this limiting obstacle is overcome by the proposed system by adding totally four such properties which effectively results in the reduction of positional bias these properties are rotation range, width shift range, height shift range, zoom range, out of which zoom range helps out the model extract minute features. Systems implemented before used Mobile Net V3 [9] as a prominent choice, however, our research deploys Efficient Net, a better alternative that yields enhanced performance. An effort has been taken by the systems before [3] for decreasing the positional bias which affects the model's ability to detect the disease seamlessly which contributes low tendency. whereas in the system proposed we extensively use the potential of data augmentation by using four properties which are rotation range, width shift range, height shift range, and zoom range, out of which zoom range plays the key role in extracting minute features. Efficient Net was used earlier too [5] resulting in better accuracies, also models such as Convent-ST-AFF have been used [2] whose works were improvised by the proposed model EfficientNetB2 along with the extensive support of image preprocessing techniques used with it, using CLAHE (Contrast Limited Adaptive Histogram Equalization) which enhances the visibility of the disease mark with the skin for better recognition for differentiating the

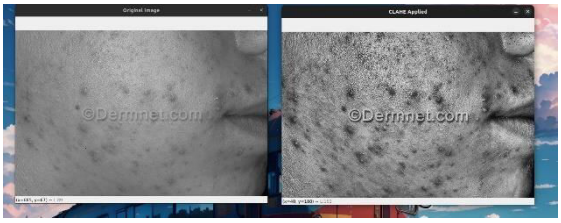

Fig 2: Contrast Limited Adaptive Histogram Equalization (CLAHE) and OTSU

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foreground and background for skin condition such as Melanocytic Nevi as successive techniques after data augmentation which gives a better opportunity to the model to learn minute details than the usage of semantic segmentation

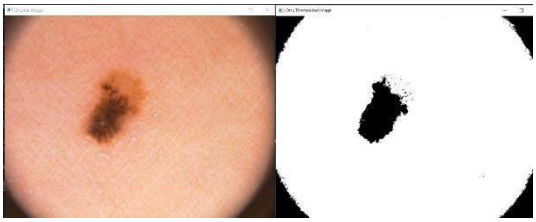

Fig 3: Before and After Image of Otsu segmentation

as a regular choice for image preprocessing [8]. Furthermore, Gaussian Mixture Models [1] have been found comparatively less efficient than the Efficient Net Model.

IV. CONCLUSION AND DISCUSSION

The system takes in an input image of 224x224 and is trained on the combination of the Keras callbacks Reduce Learning Rate on Plateau, Early Stopping and Model Checkpoint but eliminates some of the limitations of each. In addition, it provides an easier-to-read summary of the model's performance at the end of each epoch. It also provides a handy feature that enables you to set the number of epochs to train for until a message asks if you wish to halt training on the current epoch by entering "*H*" or to enter an integer which will determine how many more epochs to run before the message appears again. This is very useful if you are training a model and decide the metrics are satisfactory and you want to end the model training early. Note the callback always returns your model with the weights set to those of the epoch that had the highest performance on the metric being monitored (accuracy or validation accuracy) The callback initially monitors training accuracy and will adjust the learning rate based on that until the accuracy reaches a user-specified threshold level. Once that level of training accuracy is achieved the callback switches to monitoring validation loss and adjusts the learning rate based on that. The presence of data augmentation in the existing system uses two properties which are rotation and clipping, using only two properties of data augmentation limits the extensive potential of augmenting the data which may not reduce positional bias to a considerable level this limiting obstacle is overcome by the proposed system by adding totally four such properties which effectively results in the reduction of positional bias these properties are rotation range, width shift range, height shift range, zoom range, out of which zoom range helps out the model extract minute features.

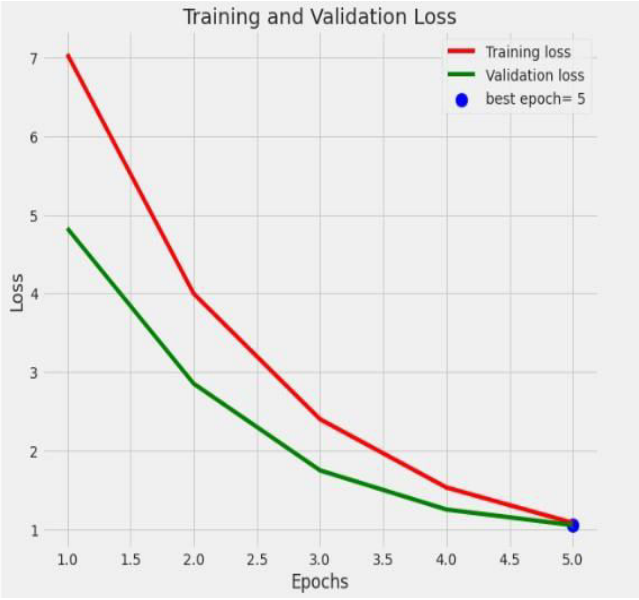

Fig 4: Training and Validation Loss

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Fig 5: Training and Validation Accuracy

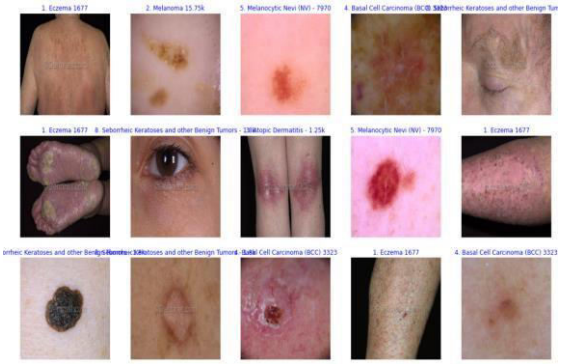

Fig 6: Skin Classes

V. RESULT

Detailed Insights from the Report

Eczema (Support: 167)

- **Precision: 0.71**: Out of all instances predicted as eczema, 71% were correct.
- **Recall: 0.64**: Out of all actual eczema instances, 64% were correctly predicted.
- **F1-score: 0.67**: This is a balance between precision and recall, indicating moderate performance for eczema classification.

Warts, Molluscum, and other Viral Infections (Support: 211)

- **Precision: 0.75**: 75% of the predicted instances were correct.
- **Recall: 0.71**: 71% of actual instances were identified correctly.
- **F1-score: 0.73**: Indicates good performance with a balance between precision and recall.

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Melanoma (Support: 314)

- **Precision: 0.98**: Very high precision, almost all predicted instances were correct.
- **Recall: 0.98**: Very high recall, almost all actual instances were identified correctly.
- **F1-score: 0.98**: Excellent performance, very reliable for melanoma.

Atopic Dermatitis (Support: 125)

- **Precision: 0.58**: Only 58% of predicted instances were correct.
- **Recall: 0.78**: 78% of actual instances were identified correctly.
- **F1-score: 0.66**: Performance is somewhat lower due to lower precision despite high recall.

Basal Cell Carcinoma (BCC) (Support: 333)

- **Precision: 0.92**: High precision.
- **Recall: 0.90**: High recall.
- **F1-score: 0.91**: Excellent performance, very reliable for BCC.

Melanocytic Nevi (NV) (Support: 797)

- **Precision: 0.98**: Very high precision.
- **Recall: 0.94**: Very high recall.
- **F1-score: 0.96**: Excellent performance.

Benign Keratosis-like Lesions (BKL) (Support: 208)

- **Precision: 0.72**: Reasonably high precision.
- **Recall: 0.85**: High recall.
- **F1-score: 0.78**: Good performance.

Psoriasis pictures, Lichen Planus, and related diseases (Support: 206)

- **Precision: 0.73**: Reasonably high precision.
- **Recall: 0.64**: Moderate recall.
- **F1-score: 0.68**: Balanced but moderate performance.

Seborrheic Keratoses and other Benign Tumors (Support: 185)

- **Precision: 0.83**: High precision.
- **Recall: 0.77**: High recall.
- **F1-score: 0.80**: Good performance.

Tinea, Ringworm, Candidiasis, and other Fungal Infections (Support: 170)

- **Precision: 0.67**: Moderate precision.
- **Recall: 0.77**: High recall.
- **F1-score: 0.72**: Balanced but moderate performance.

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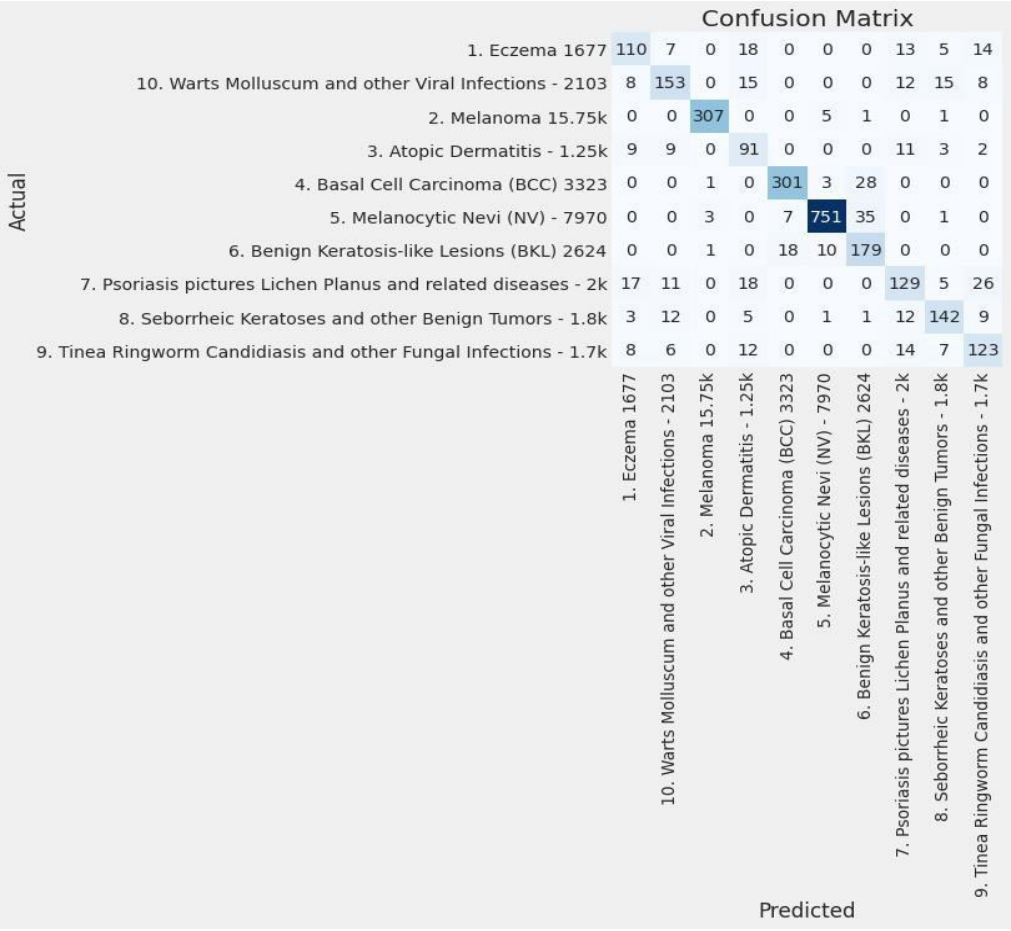
Overall Performance

- **Accuracy: 0.89**: Overall, 89% of the instances were classified correctly.
- **Macro Average (macro avg)**:
- **Precision: 0.79**: Average precision across all classes.
- **Recall: 0.80**: Average recall across all classes.
- **F1-score: 0.79**: Average F1-score across all classes. This is a simple average and does not take class imbalance into account.
- **Weighted Average (weighted avg)**:
- **Precision: 0.84**: Takes into account the support (number of true instances) for each class.
- **Recall: 0.85**: Weighted by the number of instances in each class.
- **F1-score: 0.85**: Reflects overall performance considering class distribution.



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Classification Report:

	precision	recall	f1-score	support
1. Eczema 1677	0.71	0.64	0.67	167
10. Warts Molluscum and other Viral Infections - 2103	0.75	0.71	0.73	211
2. Melanoma 15.75k	0.98	0.98	0.98	314
3. Atopic Dermatitis - 1.25k	0.58	0.78	0.66	125
4. Basal Cell Carcinoma (BCC) 3323	0.92	0.90	0.91	333
5. Melanocytic Nevi (NV) - 7970	0.98	0.94	0.96	797
6. Benign Keratosis-like Lesions (BKL) 2624	0.72	0.85	0.78	208
7. Psoriasis pictures Lichen Planus and related diseases - 2k	0.73	0.64	0.68	206
8. Seborrheic Keratoses and other Benign Tumors - 1.8k	0.83	0.77	0.80	185
9. Tinea Ringworm Candidiasis and other Fungal Infections - 1.7k	0.67	0.77	0.72	170
accuracy			0.89	2716
macro avg	0.79	0.80	0.79	2716
weighted avg	0.85	0.84	0.85	2716

REFERENCES

[1] Gupta C, Gondhi NK, Lehana PK. Analysis and identification of dermatological diseases using Gaussian mixture modeling. IEEE Access. 2019 Jul 18; 7:99407-27.

[2] Hao S, Zhang L, Jiang Y, Wang J, Ji Z, Zhao L, Ganchev I. ConvNeXt-ST-AFF: A Novel Skin Disease Classification Model Based on Fusion of ConvNeXt and Swin Transformer. IEEE Access. 2023 Oct 12.

[3] Li LF, Wang X, Hu WJ, Xiong NN, Du YX, Li BS. Deep learning in skin disease image recognition: A review. IEEE Access. 2020 Nov 11; 8:208264-80.

[4] Ahmad B, Usama M, Huang CM, Hwang K, Hossain MS, Muhammad G. Discriminative feature learning for skin disease classification using deep convolutional neural network. IEEE Access. 2020 Feb 24; 8:39025-33.

[5] Pham TC, Doucet A, Luong CM, Tran CT, Hoang VD. Improving skin-disease classification based on customized loss function combined with balanced mini-batch logic and real-time image augmentation. IEEE Access. 2020 Aug 14; 8:150725-37.

[6] Yu HQ, Reiff-Marganiec S. Targeted ensemble machine classification approach for supporting IoT enabled skin disease detection. IEEE Access. 2021 Mar 26; 9:50244-52.

[7] Mohanty A, Sutherland A, Bezbradica M, Javidnia H. Skin disease analysis with limited data in particular rosacea: a review and recommended framework. IEEE Access. 2022 Apr 7; 10:39045-68.

[8] Wang H, Yu K, Gao S, Li Q, Guan Q. Skin disease segmentation method based on network feature aggregation module and edge enhanced attention mechanism. IEEE Access. 2023 Nov 6.

[9] Back S, Lee S, Shin S, Yu Y, Yuk T, Jong S, Ryu S, Lee K. Robust skin disease classification by distilling deep neural network ensemble for the mobile diagnosis of herpes zoster. IEEE Access. 2021 Jan 25; 9:20156-69.

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