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Framework for Cosmetic Skin Disease Detection using Machine Learning and Extreme Gradient Boosting

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Abstract : In a given picture, human skin disease identification entails recognizing the skin type and the areas with the affected component of the skin. Skin ailments are frequently detected using colour pixels, textures, and edges. These characteristics are constant and quick to process. In this research, a new Skin Condition Detection Model is proposed. The RGB (Red, Green, Blue) colour model, the edges of the image, and the roughness of the skin are the three key factors used to diagnose skin disorders. The proposed model's aim is to strengthen the present skin disease detection system even while working on various skin disorders. This model employs machine learning techniques along with XGBoost in addition to the previous parameters**.**

IndexTerms **- Cosmetic Skin, Deep Learning, Imaging, Machine Learning, Skin Disease, XGBoost.**

I. Introduction

Machine learning algorithms have the capability to be profoundly engaged in all areas of medicine, from drug development to clinical decision making, dramatically transforming how medicine is conducted [1][2]. The recent popularity of machine learning algorithms for computer vision tasks comes at a good time, since medical records are being increasingly digitalized. Medical imaging is now analysed by human dermatologists, who are constrained by pace, exhaustion, and skill. A trained dermatologist takes years and a lot of money to train. The patient suffers from a delayed or incorrect diagnosis. As a result, using an intelligent, reliable, and quick & cheap machine learning system to do medical imaging analysis is ideal.

Humans are affected by skin disorders not only in terms of everyday activities, and personal relationships but also in terms of death. This disorder can also be categorized as a mental disorder, resulting in feelings of loneliness, sadness, anxiety, and even homicide or suicide. As a result, skin diseases are now one of the most important subjects in the field of medicine. Early identification is crucial in the treatment of skin disorders in order to cure the disorder, effectively limit its impact, and enhance the rate of survival [3]. People initially exploited computer-aided diagnosis for computerized skin detection of diseases based on skin disease photos to solve the issue of skin disease diagnosis and treatment. Deep learning has swiftly created computer vision as a result of the fast development of artificial intelligence technologies. In the fields of machine science, intelligent medicine, and image processing, medical image analysis of skin conditions has become an important component that has gotten a lot of attention. The image detection of skin diseases has attracted a large number of professionals and academics [4].

II. Literature Review

The performance indicators of models are the current area of research. However, a variety of environmental conditions lead to the modification of model principles and changes in performance. To make specific decisions, it is important to comprehend the variables that drive the model. There is now a significant gap in this area that has to be filled regarding the interpretability of models used to identify skin diseases. Deep learning models can be used to recognize skin diseases in order to direct clinically automated medical diagnosis. To make predictions based on input data, these algorithms are already a "black box." [5]

In this investigation, we were unable to identify any link between smoking and acne. Although smokers have been less likely to be acne patients, this link disappeared when sex was taken into account. The age range of the participants in this study was extremely broad (i.e., 15 to 40 years). As a result, we were unable to distinguish between factors that contributed to the development of acne and changes in individual habits that happened as the condition progressed [6].

[7] In order to better treat and diagnose patients, brain tumor segmentation algorithms are an important research topic. The image processing toolbox in MAT Lab is used to implement the brain tumor detection and classification successfully. MAT Lab's graphical user interface is easy to use. Other malignancies, such as breast cancer, may be detected using the suggested method. The direct health care application for segmented and edge detection is what makes these methods relevant.

[8] Skin conditions are now a very prevalent occurrence. The number of persons with skin conditions is rising quickly. Skin disease diagnosis made by humans can occasionally be arbitrary and unreliable. Computer-aided diagnosis may be utilized to

produce more accurate results that are dependable and objective. The task of detecting skin diseases is essentially one of picture categorization. Deep learning has recently been applied to numerous picture categorization tasks. As a classifier, we employed a convolution neural network (CNN). The findings show that CNN may be used to diagnose skin diseases. CNN's key benefit is that it starts to learn characteristics on its own rather than requiring us to manually create them from photos.

[9] Through this point, deep learning-based segmentation process has become a reliable technique for picture segmentation. As the first and most important step in the diagnosis and treatment pipeline, it has been routinely employed to divide homogeneous areas. We give a critical assessment of prominent algorithms for medical image analysis that have used deep-learning techniques in this work. Additionally, we list the most typical difficulties encountered and offer potential remedies.

[10] In this work, image analysing techniques used in smartphone applications to identify skin conditions have been evaluated. They were primarily created to provide a diagnosis for just one or a few particular skin diseases. Therefore, one of the unresolved problems is how to create deep learning-based systems to diagnosis additional skin illnesses. Additionally, popular benchmark datasets have not been used to test these apps. As a result, comparing their results to those described in papers is pointless.

[11] This position paper's objective is to examine and investigate cutting-edge, expansive data science methods for medical image analysis, which will aid in clinical decision-making and speed up effective medical data management. We particularly support expanding the size of image information retrieval so that interactive systems can effectively find knowledge in potentially enormous datasets of medical images.

[12] The findings demonstrated that while choosing a suitable framework for mobile skin detection of diseases, corruption errors should be taken into account in addition to accuracy. When efficiency and accuracy are important considerations, MobileNet-V3-small stands out as a viable option.

III. WORKING

Artificial Intelligence (AI) has shown promise in detecting disorders in the same way that a dermatologist does. Since the survival rate of malignant melanoma, a specific kind of skin cancer [13], has been so low, extensive study has been done on the early detection of skin cancer. The use of image processing to retrieve characteristics from images of skin disease obtained from cameras is proposed in previous work in skin disease detection [14]. A feed-forward neural network is designed to diagnose skin conditions using these characteristics. This implies that neural networks might be used to detect skin disorders.

3.1 DATASET

The term "dataset" refers to a collection of data. Acne and warts are the conditions we've chosen for our model, as seen in the diagram. The dataset was manually created using Google photos, as well as photographs from Dermnet. The pictures used to create the dataset are devoid of digital watermarking, have RGB pixels, and have been cropped in the background and hazy areas. The overall number of acne pictures is 50, whereas the total number of warts is 40. The pictures in the our model are divided into an 80:20 ratio, with 80 percent being used to train and the remaining 20% is used to test.

3.2 DATA PRE-PROCESSING

Before the data are sent into the model, image processing is very significant [15]. The image files that were downloaded at random are grouped and resampled and sorted. We used the OpenCV library to load the image files. Later, we adjusted the image to 224 * 224 * 3 three channels, indicating that the image is in RGB format. The image is scaled to make the feature extractor's calculations of pixel dimensions easier. The dataset is split into two parts: training and testing, accounting for 80% and 20% of the total respectively.

Data augmentation is a pre-processing strategy for sparse datasets. Because the restricted dataset for human skin condition diagnosis is a difficulty, we used data augmentation to construct a model with excellent accuracy while avoiding overfitting. The aim of data augmentation is to clarify and address the gap as well as to enhance the dataset. The MLXG model will be improved as a result of this approach.

3.3 FEATURE EXTRACTION

The success of skin disease categorization is dependent on the extraction of characteristics, which is a critical task. As a result, we've chosen a deep learning approach for the model, which uses each pixel in an image to automatically identify characteristics from a given image. On the basis of the Convolution Neural Network concept, the convolution performs signal processing activities that may be easily quantified as discrete spatial processing operations. A Training model and a Classification Model are required to implement the model [16].

This technique will require a huge number of skin images dataset to be entered in order for it to be accurate and reliable. Because it entails establishing and fine-tuning the essential parameters to produce the best outcomes, this approach will take more effort and time to master. The hyper parameter includes the kind of convolutional layer, number of layers, learning rate, and other hyper parameters. Apart from the challenging task of setting the parameter, training also needs the use of a high-performance GPU.

We may overcome difficulties like overfitting and develop a more flexible deep learning model by transferring knowledge learned from a source task, such as the ImageNet dataset with massive quantities of data, to the system targeted. These pre-trained models in a deep learning model can provide appropriate information and aid in the creation of the restricted histology dataset. This approach seeks to use the knowledge obtained from a set of data items and apply it to any future samples that aren't part of the data set. In this way, the model will be able to retrieve all of the learned characteristics and information in order to make predictions for new samples in the future. Learning has a number of advantages, including decreasing processing power, speeding network convergence, and enhancing network performance.

As a result, transfer learning is a more effective strategy than just randomly initializing weights to train the model for feature extraction from an input. As a result, we relied on pre-trained models throughout the procedure. The CNN model for diagnosing skin disorders has been improved by several deep learning models, such as the Model is implemented using the following:

1. VGG16
2. XGBoost (Extreme Gradient Boosting) Classifier

3.3.1 VGG16

VGG-16 is a 16-layer deep convolutional neural network. The database to load a pre-trained version of the network that has been trained on over a million photos [17]. The network can classify data into 1000 different object categories, including computers, mice, pens, and a variety of animals.

VGG16 (Visual Geometry Group) below in figure 1. is being used as the pre-trained extracting features model for this system. Because it has fewer hyperparameters and is a superior version of AlexNet, the VGG16 has been improved. Convolution + ReLU, maximum pooling, and full connection + ReLu make up the VGG16. The image processed through the first level of convolution has a fixed size of 224 * 224 * 3. (RGB channels). The image is then sent through the pile of convolution layers again, this time with a filter size of 3 * 3 and a convolution step size of 1 pixel. Because the spatial resolution of convolutional layer feeds is preserved after convolution, the padding for 3 * 3 convolutional layer inputs is 1 pixel.

The Max-Pooling layer will be used to accomplish spatial pooling in the latter. Maximum pooling is achieved by utilizing Stride 2 and maintaining the padding the same at 2 * 2 pixels. (N + 2 P - F / S) + 1 can be used to calculate maximum pooling.

Figure 1. Basic VGG16 Architecture [18]

3.3.2 XGBoost

Gradient Boosted decision trees are implemented in XGBoost. Extreme Gradient Boosting (XGBoost) is a distributed gradient-boosted decision tree (GBDT) machine learning toolkit that is scalable. It is the top machine learning package for regression, classification, and ranking tasks, and it includes parallel tree boosting. Decision trees are created sequentially in this approach. [19] In XGBoost, weights are very significant. All of the independent variables are given weights, which are subsequently put into the decision tree, which predicts outcomes. The weight of factors that the tree predicted incorrectly is increased, and these variables are put into the second decision tree. These various classifiers/predictors are then combined to create a more powerful and accurate model. It may be used to solve issues including regression, user-defined prediction, ranking, and classification.

We're using data from two distinct skin disorders to train. Making an initial prediction is the first step in adjusting XGBoost to your training set. It's possible that the forecast will be anything. Regardless of whether XGBoost is used as a regression or classification in our project, the probability of seeing skin disease predictions in training data is set to 0.5 by default.

IV. MODEL ARCHITECTURE

In our model as shown below in figure 2. we have used the pre-trained model to train our model in training phase and have added our feature extractor and classifier to classify the different skin diseases [20]. In the model architecture we have first input the images to our training model where the input images are pre-processed and then added to VGG16 feature extractor, then we have mapped the feature vector whose output is provided to classifier. This learned classifier is then forwarded to testing model which will later classify the unlabelled images of skin disease which will be provided to the testing model.

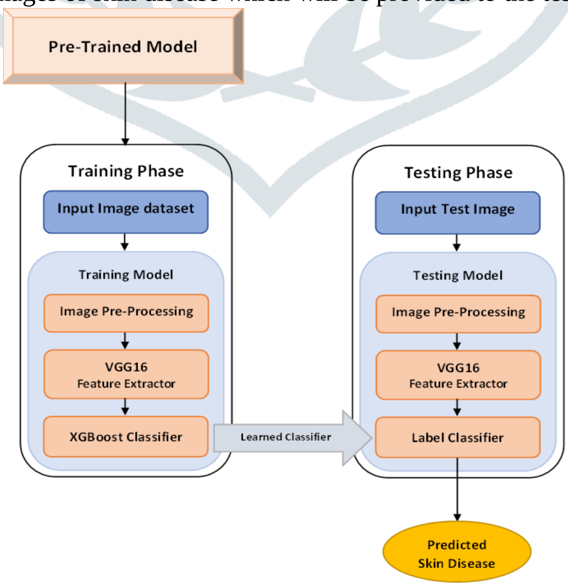


Figure 2. Proposed model Architecture

V. RESULT

The VGG16 model was trained on the proposed system using the starting weights learned from the ImageNet dataset. To stabilise the dataset, image resizing and augmentation are used for precise adjustment. BGR will be applied to the picture. All of the photos in the collection have been scaled to the required size of 224 * 224 pixels. NumPy will then be used to turn the image into an n-dimensional array. The features will be extracted from the photos by the pre-trained model. The labels of the photos were encoded using Label Encoder. We've made loaded layers non-trainable because we're working with pre-trained weights. As a result, after the feature has been retrieved using VGG16, the trainable parameter will be 0. The picture's features are retrieved, as well as the image is moulded back to its original shape. Because XGBoost's optimization is quicker than in any other algorithm and this can detect skin conditions, it was chosen as a classifier algorithm. The confusion matrix for our model is shown below in figure 3.

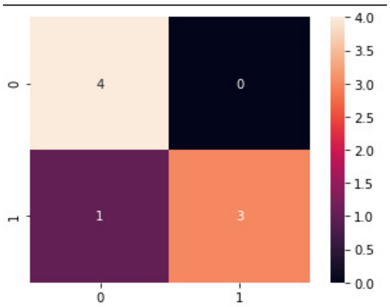


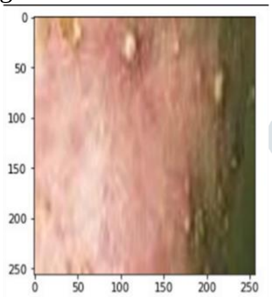
Figure 3. Model's Confusion Matrix

	precision	recall	f1-score	support
acne	0.80	1.00	0.89	4
warts	1.00	0.75	0.86	4
accuracy			0.88	8
macro avg	0.90	0.88	0.87	8
weighted avg	0.90	0.88	0.87	8

Figure 4. Accuracy of the system

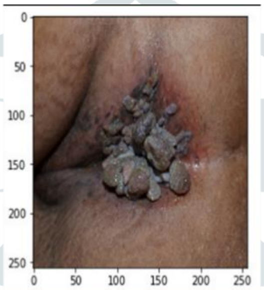
As demonstrated in the figure 4 above, our model achieves an accuracy of 88 percent. When the cases are anticipated to have a skin illness, the accuracy is determined using the True Positive (TP) criteria; true Negative (TN) whenever the cases are projected to not have a skin disease. False Positive (FP) occurs when patients are projected to have a skin illness but really have a different disease than that anticipated; false Negative (FN) occurs when cases are forecasted to not have a skin condition but actually do.

Figures 5, 6 & 7 below show the output of the image and the predicted output from the model and the actual label of the image is to be given



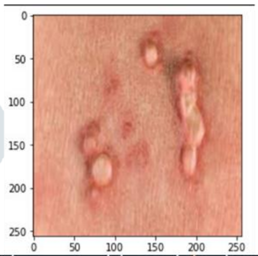
```
The prediction for this image is:  ['acne']
The actual label for this image is:  acne
```

Figure 5. Model result showing acne



```
The prediction for this image is:  ['warts']
The actual label for this image is:  warts
```

Figure 6. Model result showing warts



```
The prediction for this image is:  ['acne']
The actual label for this image is:  warts
```

Figure 7. Model result mis-interpreted value as warts instead of acne

VI. Conclusion

The paper presents the implementation of advanced architecture for skin disease prediction problem utilising VGG16 and XGBoost Classifier is highlighted in this research. Using ImageNet weights and a self-trained classifier, this architecture produced the most accurate results, with an accuracy of 88 percent. However, we believe that increasing the dataset size will improve the model's accuracy. More photos and live testing are needed to confirm our findings and strengthen the validity of our model. Technology must be used efficiently, correctly, and correctly in today's world. This initiative will aid in the development of our country's technical infrastructure.

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