Skin Type Analysis Using Inception and ITA: A Comprehensive Approach

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Abstract— This paper presents an automated and efficient system to classify skin types. For analysis of skin type, skin tone and disease have been taken into consideration. A model is proposed which combines these 2 systems to give a quick and easy analysis along with recommendation of products. The prototype works in two components, first identifies skin disease and skin tone and latter suggests products based on the analysis. This product is primarily based on inception and ITA (individual Topology angle) computation through Derm ita. The paper describes the development process and algorithm selection for required tasks. Detailed description of the proposed techniques for feature extraction, normalization and resizing have been mentioned.

Index Terms- Skin Disease, Detection, Skin Tone, Inception, ITA, Computer Vision, Feature Extraction, Classification, Pre-Processing, Image Normalization, Image Resizing. Component; Formatting; Style; Styling; Insert

I. INTRODUCTION

The skincare industry is a multi-billion-dollar industry [1]. Demand for personalized skincare products and services have been increasing rapidly. With the varied product options avail- able in market, finding appropriate skincare products can be a complicated task. Hence, the requirement of automated and efficient system for skin type classification can be beneficial. In this paper, an automated and relevant system for skin conditions and skin tones detection is preseted. Machine learning algorithms have been used by the model to analyse and classify common skin diseases like acne, rosacea, and eczema.

Skin tone, skin texture, sensitivity, and other characteristics are all taken into account while analysing skin type. Although there are models on the market that can analyse skin tone and detect skin diseases, these models are typically made for more serious issues like detecting skin cancer and function in- dividually. A model that can evaluate a person's skin type and give appropriate suggestions at the same, is required. Proposed technique is to detect skin tone and common skin problems as well as make product recommendations depending on a person's skin type, all in the same interface.

The first step of the algorithm is to take a picture using the GUI. In order to determine the user's skin tone, the model will examine the image. It will then make recommendations for products that work best with the skin tone that has been identified. Additionally, any common skin conditions like acne, pigmentation, and others will be picked up by the model, and the products will be suggested taking this into consideration.

The approach is to implement the derm ita package in Python to identify the skin tone. Tools for assessing skin tones are available in this library. Likewise, we have trained an inception model using a sizable dataset for the diagnosis of skin diseases and ITA range for skin tones. In order to evaluate the image and determine the skin tone and any skin problems, the model employs a combination of machine learning algorithms and image processing techniques.

The prototype offers a quick and practical answer to the issue of selecting appropriate skincare items for different skin types. It offers concise and straightforward suggestions for skincare products based on a person's skin tone and skin problems. It is meant to be user-friendly and accessible to everyone. The concept offers a significant advancement in the field of skincare given the development of technology and automated services, making it simpler for individuals to take care of their skin and locate products that are appropriate for their particular requirements.

II. LITERATURE SURVEY

The author, Seema et al[2]., has offered an analysis for the use of texture as a feature for skin illness in this work. The underlying properties of textures can be represented in a more straightforward but distinctive way through the application of texture analysis, which can then be utilised to segment and classify objects in a reliable and accurate manner. The analysis of images for medical diagnosis frequently uses texture-based features. This research provides a thorough analysis of texture- based feature extraction for skin disease identification. In order to extract second order statistical texture features, the authors have proposed the glcm approach. This method has been applied in a variety of situations. Glcm-based characteristics including contrast, correlation, energy, entropy, and homo- geneity, first order histogram features like mean, skewness, and energy computed from first-order histogram, dermascopic features, and colour features are among the features retrieved for disease detection. Given that there are numerous skin diseases that affect people worldwide, medical professionals may find computerised skin disease detection to be of great use. In medical image analysis, texture is a highly intriguing visual attribute that has been used to categorise images. An active area of pattern identification research has been texture analysis. This study discusses and consolidates the work on texture-based characteristics produced from the GLCM matrix for the identification of skin disorders. In the past, texture features for picture categorization have shown to be quite promising. In addition to texture-based characteristics, many studies have employed other features to input image pre- processing. Segmentation Feature Construction Vector Fea- tures of GLCM Features of First-Order Histograms Skin- Specific Qualities Features of Colour SVM/NN classifiers increase classification accuracy. The majority of the research focuses on the identification of skin cancer; however, some studies also take into account conditions including psoriasis, warts, moles, and eczema. Classifiers like neural networks and SVM are best at determining whether a picture is disease- ridden or not. Most studies indicate that overall accuracy is at or above 90%. The top five characteristics employed in all of this work are homogeneity, contrast, correlation, energy, and entropy.

In this approach, the author, Dr.Kameswara et al[3] has developed a model using CNN and an ensemble model us- ing VGG16, DenseNet and Inception. Specific skin diseases namely Actinic Keratoses, Basal Cell Carcinoma, Benign Keratosis, Dermatofibroma, Melanoma, Melanocytic Nevi and Vascular Lesions are considered. Results show that using CNN, the accuracy ranges from 71%-75%, VGG16 has at- tained an accuracy of 80.3%, DenseNet with 82.3%, Inception with 80.4% and an ensemble of VGG16, DenseNet and Inception has achieved an accuracy of 83%-85%. The en- semble of VGG16, InceptionV3, and DenseNet models uses a combination of models to improve the accuracy and robustness of skin disease detection. This model combines the strengths of three different architectures viz VGG16, InceptionV3, and DenseNet. The model collected the HAM1000 dataset from dataverse.harvard.edu . The data is transformed from images to pixels using Python Image Library to extract and classify features, The dataset is augmented by applying random trans- formations such as rotation, flipping and shifting to increase the diversity of the dataset. The dataset Random Over Sampler is used as HAM1000 consists of uncertain number of images for each disease. The dataset is them divided into features and labels. It is further divided into training and testing set which are used to train and test the model. A CNN model is created by adding 22 layers in a sequential manner, of which 5 layers are convolution layers, 2 are pooling layers, 5 dense layers, 6 batch normalisation layers, 3 dropout layers and one flatten layer. An ensemble of models which include VGG16, InceptionV3 and DenseNet architecture is created. All models are trained by specific batch size and number of epochs. Training involves taking pre-trained model and fine-tuning it for a certain task, VGG16, InceptionV3, and DenseNet have been pre-trained on the ImageNet dataset. InceptionV3 is a CNN architecture, the V3 stands for version 3. Convolution sizes 1x1, 3x3 and 5x5 are combined with pooling and normalisation layers in inceptionV3. The ensemble model including VGG16, DenseNet and Inception has the highest accuracy of 85.02%.

The goal of the author, Muhammed Reeza et al.[4], is to survey applications, colour spaces, methodologies and their performances, compensation strategies, and benchmark- ing datasets on the issue of human skin detection, covering related studies conducted over the past two decades. In order to facilitate future studies and create better approaches, several problems and difficulties associated with the task of locating skin pixels are explained in this work. The paper lists limiting elements that affect the effectiveness of skin detection algo- rithms, including complex, pseudo-skin backgrounds, imaging equipment and camera dependence, and individual and intra- personal features. The author has proposed a thorough analysis of the standard datasets, evaluation metrics, investigation of multiple colour spaces, and numerous skin detection tech- niques. The paper talks about colour spaces and how they relate to other things, like the methodology. According to the study, it is typically incorrect to assume that one colour space performs better than others. The research advises modifying the most effective skin detection models for the goal of skin segmentation rather than looking for the ideal colour space. The study discusses a number of statistical skin detection methods, divided into parametric and non-parametric methods. Non-parametric techniques can't generalise and interpolate the training data and need a sizable database for training. In con- trast, parametric approaches have a higher training complexity and call for the simulation of real distributions. The research also assesses the effectiveness of artificial neural networks (ANN) in skin identification and finds that while there is no appreciable performance enhancement, ANN systems are as successful as non-parametric approaches. The study concludes that due to their approach of confronting problems rather than offering a simple solution, spatial-based methodologies and online adaption solutions are promising in this regard.

Deep learning is a class of machine learning that automati- cally learns hierarchical features of data using multiple layers composed of simple and nonlinear modules. It transforms the data into representations that are important for discriminating the data. Due to lack of computational power, it was difficult to support the required computations, the author Bin zhang et al.[5] suggested this approach. This method was successfully applied in 2012 and outperformed previous machine learning methods for visual recognition tasks at a competitive challenge in the ImageNet Large Scale Visual Recognition Challenge. Different models such as ZENet, VGG, GoogLeNet and ResNet. The GoogLeNet model, with a structure called incep- tion, is proposed which can not only maintain the sparsity of the network structure but can also use the high computational performance of the dense matrix. The Google team improved and upgraded its version to InceptionV3. With Google's Incep- tion v3 CNN architecture pretrained to a high-level accuracy on the 1000 object class of ImageNet, researchers can remove the final classification layer from the network, retrain it with their own dataset, and fine-tune the parameters across all the layers. The neural network is not designed by humans instead the data designs itself, which proves that deep learning can be compared with professional specialists in certain fields. An AI based system is developed by researcher that allows users to install apps on their smartphones and process and judge suspicious lesions on the body by taking a picture. Images can be input to a CNN with high fidelity and important features can be automatically obtained. Simple features such as edges within the image are learned within the shallow layers. More complex high order features are learned at the deep layers near the output layer. The goal of the challenge is to support the research and development of algorithms for the automated diagnosis of melanoma including lesion segmentation, dermoscopic feature detection within a lesion, and classification of melanoma, which is also the main goal in the field of dermatology

Inthiyaz et al.'s[6] automated image-based method for clas- sifying skin issues using machine learning is presented in this work as a solution. To take into account the numerous varied properties of the processed photographs, computational tools will be applied to analyse, process, and discard image data. Skin photos are processed to improve the overall quality of the image after being first filtered to remove unwanted noise from the image. Advanced methods, such as Convolutional Neural Network (CNN), can be used to extract features from an image, classify the image using the softmax classifier's algorithm, and output a diagnostic report. The majority of the population, according to the author, are uninformed of the type and stage of a skin ailment. Some skin conditions manifest months after the disease first manifests, allowing it to thrive and spread. It is because the general public lacks knowledge of medicine. In comparison to current methods, the methodology suggested in this work is more suitable for identifying and diagnosing skin issues. The author's suggested approach is simple, time-efficient, and just calls for the acquisition of a system computer and a camera for taking pictures. This process begins with a digital image of the affected skin area, which is then analysed to identify the ailment type. The suggested work aids in the extraction of the best features from the skin photos, after which they are classed using the extremely accurate Softmax classifier. With an accuracy of 0.87, this approach appears to be very effective at identifying and diagnosing skin issues.

According to the author, Kinyanjui et al[7] skin tone is a vital factor in determining the type of skin conditions and pigments that are used in different skin tones. Classifying skin tones is usually tough, because there are various type of skin tones worldwide depending upon various factors. Today, when every aspect of world is being studied there is need of skin tone classification for various new projects special in the field of dermatology or beautification. Unfortunately, it is not always considered when developing datasets for the same. This issue can lead to poor classification performance. To overcome this, they have proposed a method that uses a Convolutional Neural Network (CNN) to estimate skin tone in images. The authors evaluated the effects of skin tone on the classification performance of various dermatology datasets, such as the HAM10000 dataset, using their proposed method. The results of their study revealed that darker skin tones were often classified incorrectly as non-cancerous lesions, but they noted that this could be corrected using their method. Hence, they suggested ITA values. According to authors, ITA is an individual typology angle to approximate skin tones in order to gain a better dataset regarding skin tones. This helped get a clear sense of skin tones. ITA works with the idea of a certain angle segment, which means a certain angle range is associated with a particular skin tone. This research has been of great help to the derma and beauty industry. However, ITA is an estimator, so there can be some minor errors.

The author Peter et al[8] emphasized the importance of unbiased and accurate skin lesion classification, it can greatly improve the detection of melanoma. In order to address performance differences between different skin tones in the categorization of melanoma and other skin lesions, the study suggests an approach for automatically labelling the skin tone of lesion images. According to observations, existing datasets might suffer from bias due to the variations in skin tone. They then proposed a method that can address this issue. Their method involves first determining the skin tone of the images. This is done through a deep neural network that is equipped with a skin colorr detector. They then use this information to adjust the threshold for classification based on the skin tone. Their method was evaluated on various publicly available datasets, such as the HAM10000 dataset, and it was able to improve the performance of darker skin tones. The findings of the experiment show that the skin tone detection algorithm outperforms currently available methods, and that 'unlearning' skin tone can increase generalization and lessen the performance gap between melanoma detection in lighter and darker skin tones. This study emphasizes the significance of eliminating bias in medical imaging datasets and offers a potentially effective method for enhancing the fairness and accuracy of CNNs for skin lesion categorization. Hence, in order to resolve performance discrepancies in melanoma classification across different skin tones, the research suggests a skin tone detection algorithm for lesion images. The importance of fairness in skin classification is ac- knowledged by the author Tmothy et al[9], as it can have a significant effect on the treatment of patients. They also note that although previous studies have shown that skin tone plays a significant role in the performance of classifiers, little attention has actually been paid to the issue of fairness in other skin tones. To address this issue, they suggest that a method be developed to measure this in order to improve the classification process. The research describes a method for estimating the approximate distribution of skin tone in public dermatology image databases. Regarding the resulting ITA val- ues, they also assessed how well dermatological classification methods performed. The authors suggest that a method can be developed to measure the fairness of a skin classification by estimating its skin tone using a deep neural framework. Then, it can evaluate the performance of the system against other skin tone groups. The distribution of ITA values in the ISIC2018 and SD-136 datasets, according to the authors, is consistent with the underrepresentation of darker skin tones. The paper provides a practical and comprehensive method for measuring the fairness of different skin tones. The findings of this study indicate that the issue of skin tone disparities in the classifiers used in dermatology is a major concern, and these disparities should be addressed in order to improve the accuracy of the diagnosis. Despite the lack of evidence for model performance bias due to dataset bias in the study, the authors recommend further research on datasets with more thorough representation.

The author Shivam et al [10] of this study talk about the importance of timely and accurate skin disease diagnosis, as these conditions can lead to serious complications if left untreated. They also note that the traditional methods of diagnosing skin diseases can be very time-consuming and can be subjective. The authors point out that classification of skin diseases is challenging because of the variety of clinical manifestations, similarity of numerous clinical symptoms, and lack of data. They suggest a technique of prototype merging using a learning algorithm that combines modelling synthesis, the mixing of at the surface and convolutional features, and an attention module to address these issues. That is, a deep learning approach be developed. The authors utilised a CNN-based system for skin disease classification, which was trained on a large dataset. Besides presenting the empirical findings, the authors also provide an extensive analysis of the CNN's deep learning framework. This includes a discussion of its architecture and an examination of the effects of varying hyper parameters on its performance. They also perform a number of other activities, such as feature extraction and parameter refining, to enhance the algorithm's capacity for classification. The results of the research show that, when applied to their proprietary dataset of pimple skin issues, the suggested model beats other techniques and also outperforms previous state-of- the-art techniques. Overall, the research points to the effective- ness of the suggested method in improving the classification of skin conditions and points to potential clinical applications. In this paper, the author Terrence et al.[11] uses an approach which utilises an Inception-v3 network pre-trained on the ImageNet dataset, it classifies skin lesions into two different scales of input images. According to dermatologist one method to classify lesions is a 3-point checklist that flags lesions as melanoma. The following are the features: Asymmetry: asymmetry of colour and structure in one or two perpendicular axes, atypical network: pigment network with irregular holes and thick lines, Blue-white structures: any type of blue and/or white colour, i.e. combination of blue-white veil and regression structures. Another method for screening for melanomas is known as ABCD parameters: Asymmetrical shape, Borders, Colour ,Diameter - melanoma lesions are typically larger than 6mm in diameter. Deep neural network models, particularly deep convolutional neural networks and its variants, are cur- rently the best performing image classification models for a wide variety of tasks and applications. The methodology in- volves fine tuning an ImageNet pre-trained Inception-v3 deep neural network on the ISIC 2017 dataset into different scales of resolution using two input images. The two scales refer to a coarse scale that captures the overall context and shape characteristics of the lesion, while the image at the finer scale reveals textural details and various low-level characteristics of the lesion that are important for distinguishing between the classes of lesion. During data preprocessing the multi scale network receive two scales of input images . The images are resized to 224x224 and 448x448 depending on the input image scale, pixel values are rescaled to a range of 0-1. All fully- connected layers from the Inception network were removed so that only the convolutional feature extraction layers remained. After the convolutional layers we added a global average pooling layer to condense the output feature maps into a 2048 element feature vector. The resulting vectors from each image are concatenated to produce a single 4096 element vector, which is then passed through a fully-connected layer with 1024 hidden units and ReLU activations. The final results from each model we combined to increase the variance of the outputs

III. METHODOLOGY

A. Skin Disease Detection

When choosing algorithms, a number of factors need to be taken into account. It is crucial to choose a model that will fit our data set as closely as possible to the ideal fit. Variables like data set size, data set type, model complexity, training duration, training resources, and algorithm performance have been taken into account. After carefully considering the aforementioned factors, the dataset and algorithm listed below havebeen chosen for our model:

1) Implemented Dataset: The dataset [13] includes skin conditions that affect the face. It includes, Acne, Acnitic Keratosis, Ezcema, Rosacea, and basal cell carcinoma.Basal cell carcinoma is a type of cancer that appears remarkably normal and is frequently disregarded. In order to prevent negligence, we have included it with the other 4 fairly commonskin conditions. A total of 625 photos in various file types, including png, jpeg, and jpg, may be found in the Train and Test directories of the dataset. Both of these directories were combined and 157 images for each disease were used to train the model. However, real-time data that was gathered through our GUI was used to test the model

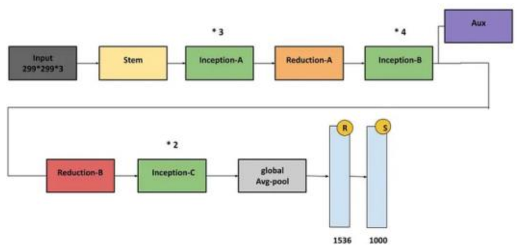


Fig. 1. Inception architecture. Adapted from [12]

B. Skin tone Detection

1) Algorithm Used: Deep learning tasks involving picture recognition and classification employ the Inception framework. It has been extensively applied to numerous computer vision tasks, including the processing of medical images. The Inception architecture has achieved excellent accuracy rates in identifying several types of skin disorders, which has demonstrated promising outcomes in the identification of skin diseases. Deep neural networks[14] are used by the Inception architecture to process the input images. It uses a novel method that combines parallel use of several convolution layers with various kernel sizes to capture characteristics at various scales. This method aids in more correctly and efficiently extracting characteristics from the input image, which improves classification outcomes. To determine the skin tone,the Python Derm ita [15] module was used. The tools in this library can be used to assess the skin tones in dermatology images. Calculating the individual typology angle (ITA) and translating the ITA value to a skin tone type are the two parts of the process. The different values of ITA were categorized in order to assess the skin tone. The Fitzpatrick scale gives us these categories, as mentioned in the Table I. The ITA uses the following equation-

$$ITA = archtan\frac{L-50}{b} * \frac{180}{\pi}$$

where b is the quantity of blue/yellow and L is brightness. In order to improve the efficiency of the model, it is advised to remove the borders of the images being used. As recommended, we removed 4% of the border before applying these approaches on the dermoscopic dataset so that the dark corners will not be included in the ITA calculation.

TABLE I
FITZPATRICK SCALE

ITA°	Skin Classification	Abbreviation Used
$ITA > 55^{\circ}$	Very Light	very lt
$48^{\circ} < ITA < 55^{\circ}$	Light2	lt 2
$41^{\circ} < ITA < 48^{\circ}$	Light1	lt1
$34.5^{\circ} < ITA < 41^{\circ}$	Intermediate2	int2
$28^{\circ} < ITA < 34.5^{\circ}$	Intermediate1	int1
$19^{\circ} < ITA < 28^{\circ}$	Tan2	tan2
$10^{\circ} < ITA < 19^{\circ}$	Tan1	tan1
$ITA \geq 10^{\circ}$	Dark	dark

**Classification Based Fitzpatrick Scale.*

C. GUI Implementation

A GUI has been developed to provide the product a clear and comprehensive appearance. The Python Tkinter package was used to build the GUI. The combination of Python and Tkinter makes it quick and simple to develop GUI apps. As suggested by their names, the buttons of our GUI carry out their task of calling the designated functions. These functions include, taking the image, calculation the skin tone, displayingthe skin tone and disease, and displaying the product recom- mendations.

IV. IMPLEMENTATION AND RESULTS

The Flow of our implementation can be observed in the Figure 2 . The project started with the collection of data and pre-processing. Various image processing techniques were used for segmentation and feature extraction. These preprocessed images were then fed into the 2 main systems of the project, the disease detection and skin tone detection systems. The outputs of these systems were further analysed for product recommendations.

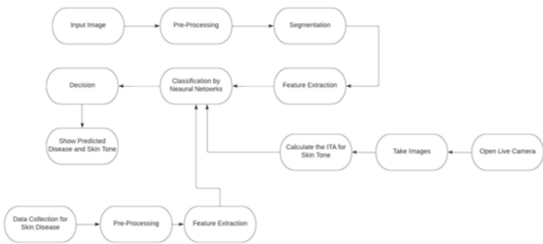


Fig. 2. GUI Interface

The model was tested with various algorithms in order to get optimized results. These algorithms included CNN, VGG16, VGG19 and Inception. Although all of these models are based on the CNN, there is a major variation in their accuracies. As seen in Table II, most accuracy is given By inception, followed by VGG19. Poor accuracies were observed for CNN and VGG 19. However, for a model like this, accuracy is not the only factor we need to consider while choosing an algorithm. Since the most important objective of our model was to give real time analysis, the run time for every model is considered. Fastest models were Inception and CNN. It is evident that inception satisfies all the needs of the model and was hence chosen for implementation.

TABLE II

V. RESULTS

Algorithm	Accuracy	Initial Run Time (per epoch)
VGG16	60%	5 Mins
VGG19	70%	7 Mins
CNN	62%	3 Secs
inception	87.5%	45 secs

*Analysis of the algorithms.

For building the GUI interface in python the tkinter module has been used. When the GUI code file is run five options are present which include Take Image, Display Image, Calculate Skin Tone, Products and the Exit button. The Take Image function uses OpenCv and haarcascade frontalface default.xml file. A live camera is used to take image.

Fig. 3. GUI Interface

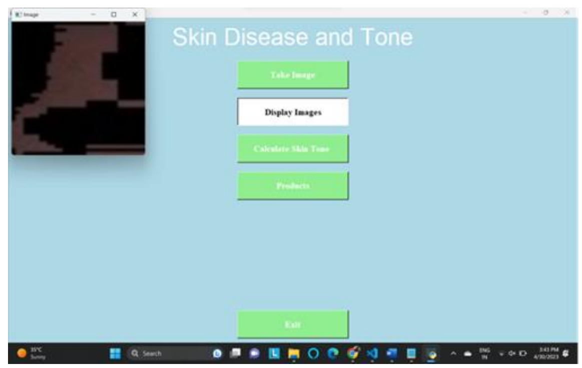
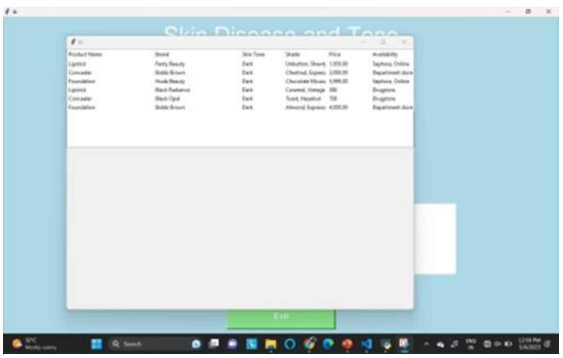


Fig. 4. GUI window displaying detected skin

A separate code file has been written which contains the code for skin disease detection. The file is run and trains the model for 10 epochs. The model is then saved in a ".h5" file. This .h5 file contains the model and the pre-trained weights of the model. In the GUI, this .h5 file is loaded using the load model function. First, the disease names that are present in the model are defined, and the functions that will be used in the GUI.

The Take Image button opens the camera for 4 seconds and takes 5 images which is an image per second, which will be extracted per second from the video frame. These images are then saved as PBL1 to PBL5 in the main folder. The Display Images Button will display the images after the operation of finding the ROI which identifies the skin and eliminates all the non-essential features before displaying the image. The Calculate Skin Tone Button uses the get kinyanjui type module which is imported from the derm ita package it will calculate the ITA for the images and give us the skin tone for the images and the skin disease. If there is a probability of less than 0.5 or 50% present for the skin disease, then it will show No disease detected as the predicted disease. The Products button calls and open the Products.py file, which matches the outcome from the get kinyanjui type which is the deteted skin tone, with the products in the csv file linked with the Products.py file. It displays all the data matching the skin category that matches the skin tone.



Another code file is created, to define the fuction that displays the products for the detected skin type. The GUI displays the Product name, Brand, Skin Tone, Shade, Price and Availability of the product. The GUI is saved in a python file named Products.py. To summarize, the proposed technique takes the image through a live camera, then detects only the skin, stores the image and then displays if any skin disease is found and even displays the skin tone detected in the images. With skin tone and disease, the system also displays a medical recommendation according to the disease found or any beauty product according to skin tone or minor skin conditions such as acne.

CONCLUSION

With the increasing numbers of minor as well as major skin diseases, the need for accurate and efficient diagnosis methods is must. The use of such AI based system can help with the very same purpose. The strengths of this system include its ability to detect skin diseases, calculate accurate skin tone, and recommend beauty product accordingly. The shade of skin illustrates type or kind of skin condition. Hence considering the skin tone, the system can diagnose with increased accuracy. The use of individual typology angle (ITA) to approximate skin tone is an accurate proposal which can improve the performance of the model.

The prototype is designed to be easy to use by common customers and user friendly. The GUI interface is simple, and the buttons are self-explanatory. The system uses image processing techniques to filter the skin down, OpenCV and haarcascade frontalface default.xml to detect face. The skin tone is then detected by calculating ITA. A pre trained machine learning is used to detect skin disease is present or not. Then a list of beauty products based on the skin tone detected or any minor skin condition like acne is recommended. The model displays the product name, brand, shade, price, and availability making it easier for the user to purchase the product offline or online.
After training and testing, limitation of the system is that it relies on a certain common dataset of the dermatology industry. It may not include all the skin conditions or skin tones out in the world. There is further requirement of necessary research to generalize the system.

Overall, the technique to automatically detect skin disease and skin tone through a live camera reflects big impact and help towards dermatology as well as beauty industry to personalize skin care solutions with accuracy. This model will also help the dermatology industry to reduce dependency on medical personnel-based methods and increase availability and efficiency of the treatment and diversify the choice to the world. It has potential to bring in a change where users have hassle-free, interesting, and comfortable shopping experience. This system has ability to benefit patients as well as doctors and beauticians in the near future.

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