Empowering Skin Wellness with AI Predictions and Expert Consultation

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Abstract— An overview of AI-based skin disease categorization and segmentation is provided by this project. For this objective, a variety of AI techniques are investigated, including machine learning and deep learning models. The accurate separation of skin lesions from surrounding healthy tissue is addressed by the segmentation component. For precise lesion segmentation, artificial intelligence (AI) approaches such as convolution neural networks (CNNs) and image processing algorithms are applied. It is investigated how segmentation and classification approaches might work together to analyze skin diseases in a more thorough manner. Skin disorders are categorized by grouping different dermatological conditions according to their outward appearance, such as color, texture, and pattern. This project categorizes diseases, suggests products or further treatments for certain diseases, and allows you to purchase the recommended products at the same

Index Terms- Skin wellness, dermatological conditions, Doctor consultation, Treatment plans, Telemedicine

I. INTRODUCTION

Skin conditions impact millions of individuals worldwide, spanning all age groups and demographics, and pose a substantial burden on public health. Effective treatment and management of skin disorders depend on a fast and correct diagnosis. The development of artificial intelligence (AI) and machine learning (ML) technology has led to the emergence of automated techniques for classifying skin diseases, which hold great promise as diagnostic tools for dermatologists.

Skin disorders are categorized by grouping different dermatological conditions according to their outward appearance, such as color, texture, and pattern. In the past, this work mainly depended on dermatologists' knowledge, which can be laborious and subjective. However, recent advancements in deep learning and computer vision have made it possible to create automated categorization systems that can examine pictures of skin lesions and offer.

II. PROBLEM STATEMENT

Traditional skincare procedures are inadequate in providing precise, effective, and customized treatments. This presents a challenge for incorporating AI predictions and professional consultations into skin wellness. Frequently, existing techniques depend on broad guidelines that might not take into account individual variations including skin type, genetic predispositions, and environmental influences. As a result, those seeking skincare solutions may incur needless costs, experience prolonged suffering from skin conditions, and receive ineffective treatment. Further exacerbating the issue and depriving many people of appropriate skin health advise is the restricted availability of dermatological services in some places. Progress towards reaching the best possible outcomes for skin wellness is also hampered by skincare techniques that are not continuously improved upon and refined. It is therefore imperative that a thorough and creative strategy that maximizes the potential

III. NEED FOR THE SYSTEM

a. Enhanced Access to Dermatological Care: A lack of dermatologists, long appointment wait times, and geographic restrictions are just a few of the obstacles that millions of people experience when trying to get timely dermatological care. Regardless of a person's location or access to healthcare, an integrated solution that combines AI prediction with professional consultation can offer timely and easily accessible dermatological guidance.

b. Enhanced Diagnostic Precision: Conventional techniques for identifying skin conditions frequently depend on dermatologists' subjective visual assessments, which can result in discrepancies in diagnosis and suggested courses of action. Prediction models powered by AI can objectively and consistently assess skin scans, boosting the diagnosis accuracy and complementing dermatologists' skills.

c. Early Detection and Prevention: Prompt identification of skin disorders is essential to efficient care and avoidance of consequences.

IV. OBJECTIVE

By improving precision, effectiveness, and customization, the goal of incorporating AI forecasts and professional advice into skin wellness is to completely transform skincare. Artificial intelligence (AI) forecasts examine enormous volumes of data to deliver remarkably precise information on a person's skin condition, possible problems, and efficacy of therapy. This effectiveness shortens the time it takes for people to address their skin concerns by enabling speedier diagnosis and treatment planning. Furthermore, customized skincare solutions that take into account aspects like genetic predispositions, skin type, allergies, and sensitivities can be achieved by fusing AI predictions with professional consultations. Individuals will receive information and help tailored to their own situation thanks to this individualized approach. Furthermore, skincare solutions are now more widely available to a wider demographic, regardless of geography, thanks to the accessibility of AI-powered skin health platforms.

V. SYSTEM DESIGN

Interface for Users (UI): Accessible through a mobile app or the web, this interface is user-friendly. Interface to record symptoms in text and upload pictures of the skin. There are options to choose your preferred language and give permission for AI prediction and professional advice.

The AI Prediction Module: The incorporation of machine learning algorithms, namely convolutional neural networks (CNNs), to anticipate skin diseases.

noise reduction, normalization, and picture enhancement preprocessing pipeline. based on features retrieved from skin photos, trained models for multi-class classification of skin diseases. Module on Expert Consultation: Expert consultation and assessment of AI forecasts by dermatologists on a secure platform. Security of data and privacy are ensured by access controls and authentication procedures. Video conferences and text chat are examples of real-time communication platforms that allow users and dermatologists to engage.

Database Administration: User profiles, skin photos, textual symptom descriptions, forecasts, and consultation records are all stored in a database. resilient and scalable architecture to manage high data volumes and user interactions. application of data privacy laws, such GDPR adherence, to protect user data

Workflow and Integration: AI prediction and expert consultation modules are seamlessly integrated to offer a seamless user experience. System for managing workflows that will facilitate communication between dermatologists, AI models, and users. Users can receive automated notifications to let them know when AI predictions are ready and when expert consultation is about to happen or has finished.

Mechanism of Feedback: Users can rate and discuss AI predictions and expert consultation experiences through a feedback loop. To enhance AI models and service quality, system performance and user comments are continuously monitored.

Regulation and Compliance: compliance with laws and guidelines governing healthcare IT systems, such as HIPAA compliance regarding data security and privacy.

assisting in the enforcement of national and international laws governing medical software and medicine through collaboration with legal and regulatory specialists.

Scalability and Efficiency: infrastructure that is scalable to meet rising user demand and data volume. strategies for performance optimization, including as resource provisioning, load balancing, and caching, to guarantee system dependability and responsiveness.

Analytics and Monitoring: Tools for keeping tabs on user interactions, system performance, and AI model accuracy. Analytics dashboard to produce insights on the usage trends, demographics of users, and results of expert consultations and AI predictions. application of analytics data to support resource allocation, system optimization, and strategic decision-making.

VI. METHODOLOGY

In this research, we offer an image processing and machine learning approach for classifying dermoscopic images as benign or malignant. Picture Archive: The ISIC website's publicly accessible image library is where the database is downloaded. The RGB dermoscopic images from the ISBI-2016 challenge, along with their labels and segmentation ground facts, were put in the database.

Pre-Processing: Pre-processing is done on ISIC-ISBI data set images to make them more uniform among their various artifacts. important. Re sizing the image, removing noise, stretching the contrast, converting RGB to grayscale, and removing hair were all part of the pre-processing. All of the photos were downsized to 767x1022. A 3-by-3-by-3 median filter is used for noise removal. A new approach is suggested for contrast enhancement. Segmentation outcomes in the following phase are considerably improved by contrast enhancement. The mean and standard deviation of the pixel intensities in the photos serve as the basis for the suggested contrast stretching. Input image values are calculated using the methods found in (1) and (2) to determine the minimum and maximum intensity values, or "Low in" and "High in" values.

Low in = Avg -ı*N (1)
High in=Avg + ı*N (2)

Where,
Avg = Average
N = 0.4
Intensity values are then mapped in the output image from 0 to 255. Contrast stretching is performed on R, G, and channels separately which are later concatenated to RGB to gray conversion is perform next. For removing hairs bottom-hat filtering is performed, then those pixels which have been filtered are replaced by neighboring pixels.

Segmentation: After the Pre-Processing, segmentation is to extract the region of interest i.e. skin lesion. We used the thresholding algorithm for the segmentation of

TABLE I. EXTRACTED TEXTURE AND COLOR FEATURES

Texture features	Skewness	Mean	Contrast	Energy	Homogeneity	Standard
	Root Mean Square	Variance	Smoothness	Kurtosis	Correlation	Entropy
	Inverse Difference Movement					
Color Features	Mean R	Mean G	Mean Blue	Variance R	Variance G	Variance Blue
	Kurtosis R	Kurtosis G	Kurtosis	Skewness R	Skewness G	Skewness Blue
	Mean hue	Mean Saturation	Mean	Variance Hue	Variance	Variance Value
	Kurtosis H	Kurtosis S	Kurtosis V	Skewness H	Skewness S	Skewness V
	Mean L	Mean A	Mean B	Variance L	Variance A	Variance B

grayscale Pre-Processed images. OTSU thresholding aims to find the threshold and classify pixels into two classes so that within-class variance is minimum (between-class variance is maximum). Background triangles that exist in a few images on four sides are then removed by creating a mask and adding it to the binary image. Later the image is inverted to make the skin lesion white and the background to be black. Flood fill operation on 4-connected pixels in the background is performed to remove holes. A morphological opening is then done to remove small objects having pixels fewer than 2000. The lesion border is smoothened using opening operation first with a disk-shaped structuring element of radius 20 followed by a closing operation with the same structuring element.

Features reduction and extraction :
Texture, shape, and color characteristics are taken out of the segmented skin lesions after segmentation. Segmented lesions mapped on original pictures were used to extract the texture features are first transformed from RGB to grayscale. Grayscale images are then subjected to two-dimensional wavelet decomposition of level 3, using the mother wavelet as Daubechies (db4). New, smaller-sized images are

produced by the level 3 wavelet decomposition's low pass approximation coefficients matrix (CA). The gray level co occurrence matrix of the approximation coefficients matrix is then used to derive the texture features. Table 1 displays the total number of retrieved texture characteristics, which is 13.

As seen in Table 1, a total of 36 color features are extracted utilizing the RGB, HSV, and LAB color spaces.

SMOTE Data Collection :
There is an issue with class imbalance in the ISIC-ISBI data. There are 20% of "malignant" data and about 80% of "benign" data. Thus Since it has received more training on benign data, any classifier trained on this data will be more skewed or prejudiced. Poor training, poor training accuracy, and poor classification accuracy on test data would follow as a result. Therefore, balancing the data is necessary initially. The resulting feature vector is subjected to the Synthetic Minority Over Sampling (SMOTE) approach for this reason [11]. Data from the SMOTE technique were found to be 50% malignant and 50% benign.

The feature vector is extracted using all of the ISIC-ISBI data set's training and test data. Next, data balancing is accomplished using the SMOTE approach.

Characteristics uniformity :
The "Linear Scaling to Unit Variance" approach is used to normalize the features vector [12]. Standard deviation and average is computed for each column in the feature vector. To obtain the zero mean feature vector, the average of each column is then deducted from the corresponding column of the original feature vector.

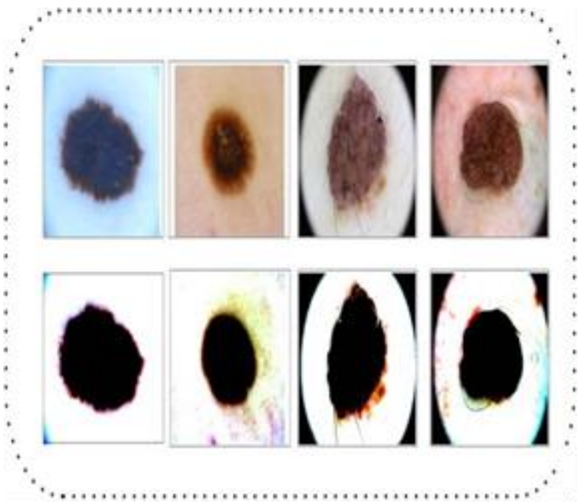
The feature vector of unit variance is then obtained by dividing each column's zero mean feature vector by the column's standard deviation.

Characteristics :
Scaling and choosing the method features are scaled ensures that every feature in the feature vector is normalized within a range of 0 to 7 utilizing the Mapping Algorithm Min-Max
This research suggests a unique strategy for classifying skin cancer employing wrapper methods as feature selection techniques. Using the training procedure as part of the evaluation function, the wrapper method looks for a subset of characteristics that are both weakly and strongly relevant and that enhance performance. The wrapper technique was put up by George H. Johnetal. as a solution to the problems of improving accuracy and identifying a subset of attributes that are most relevant.

Classification :
As the last stage, we divided the data into benign and malignant categories.
several classifiers, such as SVM and the quadratic discriminant After that, training is conducted using (Medium Gaussian), and Random Forest, and test data is used to assess how well they performed. Test data is then used to evaluate classifier models. SVM finds the hyperplane with the largest margin by classifying the data into distinct groups. For Random Forest classification, the suggested features selection based on wrapper approaches yields impressive and promising results. The Random Forest classifier uses 500 decision trees, and classification is carried out according to the majority votes of decisions made by various trees. Using data samples, the Random Forest technique creates decision trees, and the predictions from each tree are put to a vote to determine the categorization.

VII. RESULT

The segmentation results in relation to ground truths are displayed. The ISIC-ISBI2016 classification accuracy results dataset with the classifiers 85.50%, 88.17%, 90.84%, and 93.89% utilizing the SVM (Medium Gaussian), Quadratic Discriminant, and Random Forest methods, on the other hand. Figure 4 displays the ISIC-ISBI 2016 confusion matrix using the Random Forest classifier. Five percent are incorrect out of 114 malicious predictions, with 94.7% being correct. Sixty-eight percent of the 148 benign guesses are incorrect, whereas 93.2 percent are true. 5.2% of the 144 benign participants were correctly predicted to be malignant, whereas 95.8% of the subjects were correctly predicted to be benign. Eighty-five percent of the 118 malignant subjects are classified as benign, whereas ninety-one percent are correctly classified as malignant. There are 6.1% incorrect guesses out of a total of 93.9% right guesses.



CONCLUSION

This paper implements a novel machine learning and image processing approach for the categorization of skin cancer. Initially, a new technique for contrast stretching based for the improvement of dermoscopic images is suggested based on the mean and standard deviation of pixels. After that, segmentation is carried out using OTSU thresholding. The second phase involves extracting the shape, color, and texture features; the PCA is then used to minimize the shape features. The SMOTE sampling approach is employed to address the issue of class imbalance seen in the ISIC dataset.

After features are scaled and standardized in the third stage, a novel method of feature selection based on wrapper techniques is suggested for choosing the best features.

An accessible dataset is used to test the suggested system.

TABLE 2 CLASSIFICATION RESULTS USING DIFFERENT CLASSIFIERS

Classification Algorithm	Accuracy (%)
SVM	88.17
Quadratic Discriminant	90.84
Random Forest	93.89

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