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# SmartSkinAI: Innovations in Dermatological Preliminary Diagnosis using AI

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**Abstract -** Dermatological conditions are becoming predominant across the globe.People in different geographical locations suffer from various skin diseases such as acne, melonama, eczema and many more.However, they are unaware about the severity of these skin diseases as they may worsen with time.Preliminary diagnosis of skin conditions play a vital role in prediction of the disease. Skin disease diagnosis at present includes a series of pathological laboratory tests for the identification of the correct disease. At the moment, AI-powered diagnostic technologies can help physicians in making quicker and more precise diagnoses.This research proposed an efficacious solution by implementing Convolutional Neural Network architecture MobileNet(v2).The dataset is gathered from various sources to collect images of ten different skin disorders.Then classification techniques are implemented for predicting the type of skin disease.The trained model is deployed on the web using Django framework and the recognition of skin diseases can be done remotely using this system. Out of different performance evaluation measures,accuracy and loss is calculated to verify the working of model. Our model comprising of MobileNet(v2) achieved accuracy upto 99.00%. Moreover, we proposed and implemented a web-based model for the real-time recognition of skin diseases. This approach can aid health professionals by recognizing different skin diseases more efficiently and making the diagnosis process more user-friendly for the patients.

***Key Words*: Convolutional Neural Network (CNN), skin disease, MobileNet V2, classification, preprocessing,train-test split***

## I. INTRODUCTION

Skin disorders affect a significant portion of the global population, presenting challenges in timely and accurate diagnosis. Leveraging the advancements in artificial intelligence (AI), our research endeavors to address this issue by introducing an innovative AI-based tool for the preliminary diagnosis of dermatological manifestations. This system employs a Convolutional Neural Network (CNN) model with the MobileNet(v2) architecture, comprising 12 layers, to analyze uploaded or live photos and provide users with rapid insights into potential skin diseases.This research uses data from various data sources to collect images of 10 different types of skin disorders.

The functionality of our AI-based tool revolves around two key options: users can either upload a photo of the dermatological manifestation or capture a live photo using their device's camera. Upon submission, the system utilizes its trained CNN model to detect the potential skin disease and offers a concise description of the identified condition. This initial diagnostic information serves as a valuable first step in guiding individuals towards understanding their skin concerns.

To enhance user engagement and provide a more comprehensive understanding, our system offers two distinct paths for further exploration. Users can choose to delve deeper into the specifics of the predicted disease by selecting the "Get More Info" option. Here, a detailed description of the identified condition is provided, with the added flexibility of selecting preferred languages for comprehension. The ability to choose from multiple languages ensures accessibility and inclusivity, enabling users to comprehend the detailed information in a language they are comfortable with.

Additionally, our AI-based tool offers a practical approach for those seeking home remedies. Users opting for the "Home Remedies" feature are presented with a curated list of potential remedies for the identified skin condition. This not only empowers individuals with actionable steps for self-care but also contributes to raising awareness about home-based solutions for common dermatological issues.

## II. LITERATURE REVIEW

Shuchi Bhadula proposed a system with a database of 4 common skin diseases, using which patient can self-diagnose and get some prior knowledge of their skin disease before consulting the dermatologist.This system can be accessed even in most remote areas of the country. The proposed system provides an easiest and convenient method of skin disease detection where the patient provides a picture of the infected area as an input image and any further analysis is done on this input image. However, this system lacks transparency which make it challenging to understand the diagnosis.

Aijaz S. F. proposed a deep learning-based application where different categories of skin diseases are classified. Two different deep learning models CNN and LSTM were used in this approach. For better results, different pre-processing techniques such as augmentation, enhancement, and segmentation were employed in this study and achieved an accuracy of 84.2% and 72.3% for CNN and LSTM, respectively.There are implications for further research in relation to the existing proposed deep learning application which can lead to enhancement of methods in biomedical imaging. The existing application can also be applied to other skin disorders along with being integrated with other deep learning techniques like RNN. Moreover, research pertaining to Psoriasis Area and Severity Index (PASI) scoring can also be carried out in the future.

K. Sreekala proposed a system that implements the Structural Co-Occurrence matrices for feature extraction in the skin diseases classification and the preprocessing techniques are handled by using the Median filter, this filter helps to remove the salt and pepper noise in the image processing. Thus, it enhances the quality of the images, and normally, the skin diseases are considered as the risk factor in all over the world.This proposed approach provides 97% of the classification of the accuracy results while other existing model such as FFT + SCM gives 80%, SVM + SCM gives 83%, KNN + SCM gives 85%, and SCM + CNN gives 82%.However, support vector machine's accuracy should be increased in classifying skin illnesses.

Adicherla Rushi proposed the system which can extract important features from skin images and classify the diseases with high accuracy. The integration of CNN and SVM

provides a powerful tool for skin disease diagnosis, as it leverages the strengths of both techniques to achieve high performance.The proposed algorithms presented in this study exhibit excellent performance and low time complexity, making them suitable for various applications in ultrasound skin imaging and computer-aided diagnosis systems. However, it is important to note that skin disease diagnosis using CNN and SVM is still a developing field and there is ongoing research to improve the accuracy and reliability of the system.In future research, integrating the proposed methods with suitable classification algorithms to develop a more reliable and accurate computer-aided diagnosis system can be implemented.

## III. METHODOLOGY AND PROPOSED SYSTEM

### A. DATA PREPROCESSING

Data preprocessing involves cleaning, transforming, and organizing raw data into a format suitable for further analysis.In the initial phase of our model development, we integrated data from multiple sources into a unified dataset.Then we imported essential Python libraries to facilitate seamless data processing and analysis. Following this, we transformed the raw image data into RGB format, ensuring uniformity in representation for subsequent processes.The categorical variables were converted into numerical representations using One-hot encoding technique.As part of the preprocessing pipeline, we normalized the pixel values of the images by dividing them by 255. This normalization step standardizes the input data, enabling the model to converge faster during training and preventing issues related to varying scale.

To augment the dataset and enhance the data quality,the data was transformed into a consistent format by applying transformations like rotation, scaling, cropping or flipping to the images. Furthermore,the target variables were selected followed by splitting the dataset into training and testing sets using a ratio of 80:20 through the train_test_split method for creating a robust and reliable model. By performing these preprocessing steps, we ensured that the data is clean, consistent, and well-structured, enabling more accurate analysis and model building.

### B. CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Networks (CNNs) typically consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The model's internal structure comprises 256 hidden layers and 10 output layers, where Rectified Linear Unit (ReLU) activation functions are employed for the hidden layers to introduce non-linearity. The choice of softmax activation for the output layers enables the model to produce probability distributions across the various disease classes, facilitating multi-class classification. With 256 hidden layers, the network is exceptionally deep, enabling it to learn complex features from input images through hierarchical layers of feature extraction and abstraction.

The 10 output layers typically correspond to the number of classes or categories in the classification task. Each output neuron represents the probability or accuracy associated with a specific class.

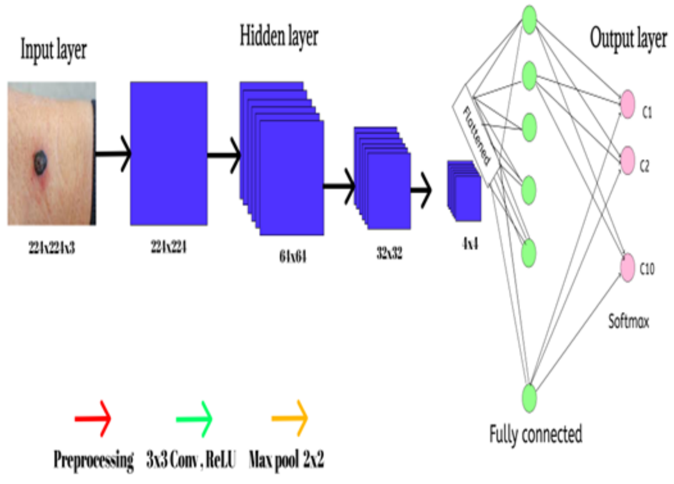



**Fig -1**: Convolutional Neural Network architecture

## C. MOBILENET V2 ARCHITECTURE

The MobileNet V2 architecture is a lightweight and efficient convolutional neural network commonly used for mobile and edge devices. It utilizes depthwise separable convolutions, which split the standard convolution into separate depthwise and pointwise convolutions, significantly reducing the number of parameters and computational cost.MobileNetV2 also incorporates inverted residuals and linear bottlenecks, which improve the flow of information through the network while maintaining computational efficiency.The architecture consists of several building blocks, including inverted residual blocks with shortcut connections, expansion layers, and squeeze-and-excitation modules.MobileNetV2 achieves a good balance between model size, accuracy and computational efficiency.

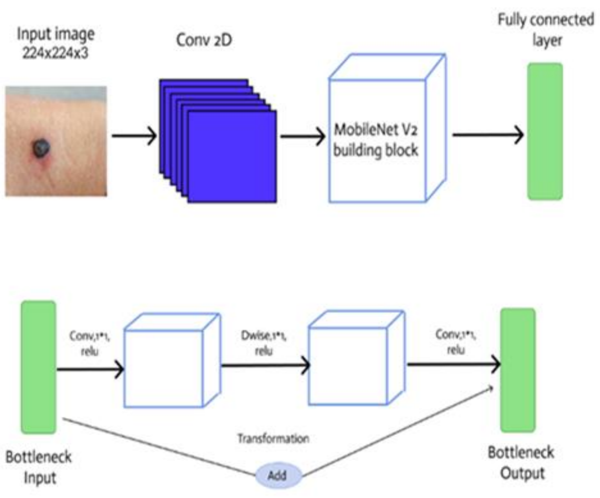



**Fig -2:** MobileNet v2 architecture

## D. SYSTEM OVERVIEW

In the design of our model, we have opted for MobileNet V2 architecture coupled with a Convolutional Neural Network (CNN) algorithm which empowers the model to extract meaningful features from the input data, particularly beneficial for image-based tasks such as disease prediction.The system consists of User Interface (UI) and CNN model for prediction of diseases along with the image preprocessing,feature extraction and classification blocks.The training process is carried out in this CNN model after splitting the dataset randomly through train-test split method.

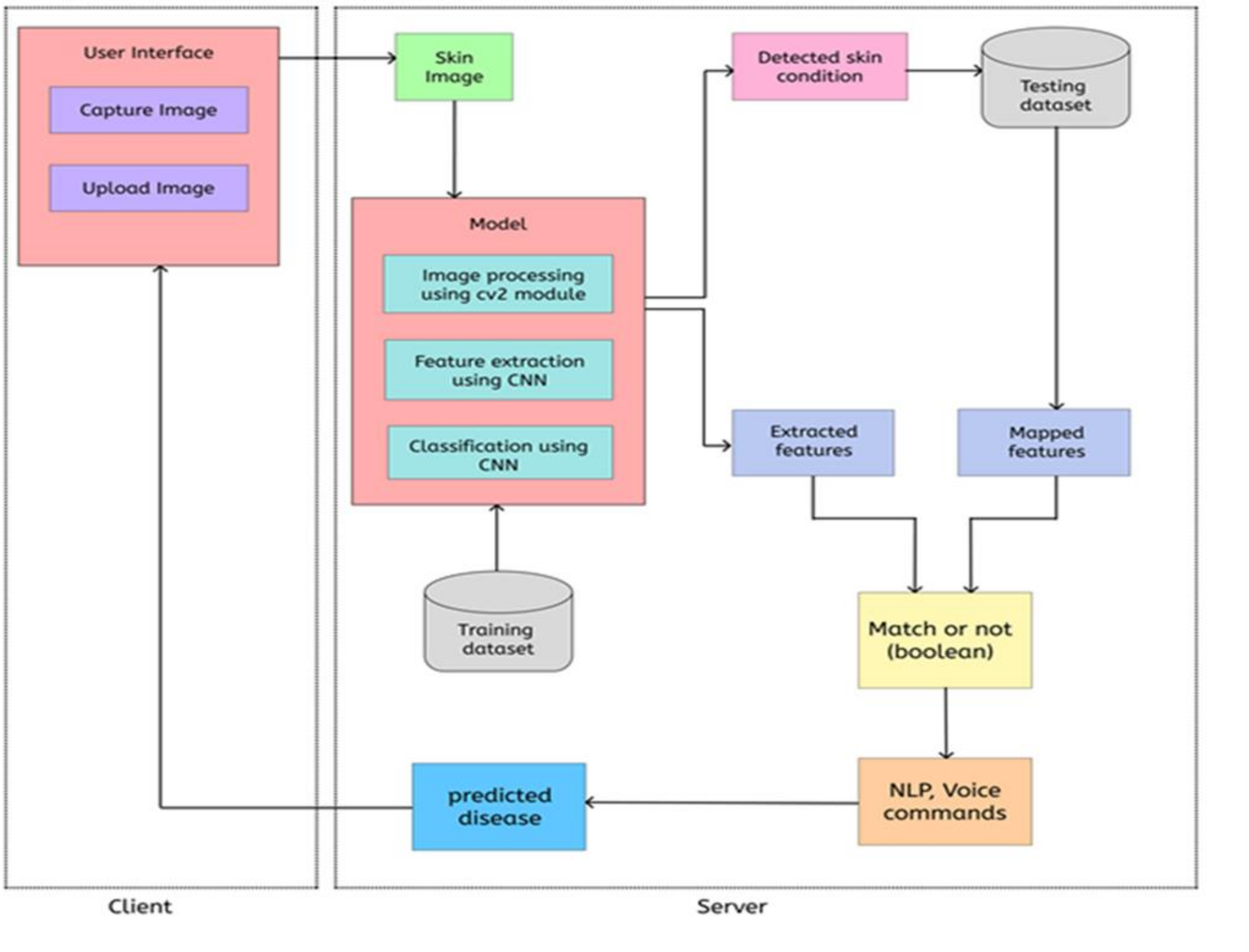
In the training phase, a batch size of 64 is employed, ensuring that the model processes data in manageable chunks. The training process spans 20 epochs, indicating the number of times the entire dataset is passed forward and backward through the network. In each epoch, the model sees the entire dataset, learns from it, and updates its parameters accordingly. Increasing the number of epochs allows the model to see the data more times, potentially improving its ability to learn complex patterns and generalize well to unseen data.This balance between batch size and epochs is crucial for achieving convergence and optimal learning.

However, training for too many epochs can lead to overfitting.To address the challenge of overfitting, we incorporate an early stopping callback function during training. This mechanism monitors the model's performance on a validation set and halts the training process if there is no improvement, preventing the model from learning noise and enhancing its generalization capabilities.

Following the architectural and algorithmic choices, the model is compiled using the Adam optimizer. Adam computes adaptive learning rates for each parameter by combining momentum and RMSProp techniques.It maintains moving averages of gradients and squared gradients to adaptively adjust the learning rates and account for the sparsity and scale of gradients. Adam's adaptive learning rate strategy makes it well-suited for a wide range of deep learning tasks, providing fast convergence and robust performance with minimal hyperparameter tuning. That is why Adam is favored over Stochastic Gradient Descent (SGD) optimizer.

Once the model is compiled followed by fitting the model,it performs classification tasks and the features extracted after classification are compared with mapped features.Then it predicts the disease and final results are displayed on the User Interface.With these meticulous design considerations, our model is well-equipped to predict diseases accurately, harnessing the capabilities of MobileNet V2, CNN, and thoughtful optimization techniques.

**Fig -3:** Proposed system




### E. SYSTEM OVERVIEW

Our system offers two functionalities "Get More Info" and "Home remedies" , which users can access after prediction of their skin disease.The first added feature is "Get More Info" option which serves as a valuable tool for individuals seeking additional information on skin disease.Our system will provide users with valuable information on symptoms, conditions, treatments, preventive measures, lifestyle modifications, and self-care practices. This enables individuals to take proactive steps towards improving their health and well-being.

The second important feature is "Home remedies" which serves as a convenient and accessible resource for individuals looking to address common skin issues or promote well-being using natural and often household ingredients. Many home remedies utilize ingredients that are readily available at home or can be purchased inexpensively from local stores.Our system will provide home remedies involving natural ingredients such as herbs, spices, fruits, and vegetables, which are generally safe and well-tolerated by most people. These remedies are tailored to individual preferences, needs, and sensitivities.

For example, the system will suggest home remedies such as aloevera and turmeric mask, honey and cinnamon mask etc for acne. They can complement conventional treatments and support the body's natural healing processes. They may provide relief from symptoms and enhance treatment outcomes without causing side effects. This makes them cost-effective alternatives to over-the-counter medications or medical treatments, especially for individuals on a tight budget.

## IV. RESULTS

The performance of the proposed working model is evaluated by measuring some metrics like accuracy, precision, recall, F1 score and support.This model has achieved an accuracy of 79% on real-time data.

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| Classes | precision | recall | f1-score | support |
|---|---|---|---|---|
| Eczema | 0.54 | 0.61 | 0.57 | 339 |
| Melanoma | 0.99 | 0.92 | 0.96 | 623 |
| Atopic | 0.47 | 0.64 | 0.54 | 252 |
| BCC | 0.94 | 0.93 | 0.94 | 655 |
| Nevi | 0.94 | 0.96 | 0.95 | 1592 |
| Keratosis | 0.77 | 0.84 | 0.81 | 402 |
| Psoriasis | 0.46 | 0.52 | 0.49 | 406 |
| Seborrheic | 0.78 | 0.59 | 0.67 | 382 |
| Tinea | 0.78 | 0.40 | 0.53 | 362 |
| Warts | 0.61 | 0.69 | 0.65 | 401 |
| accuracy | | | 0.79 | 5414 |
| macro avg | 0.73 | 0.71 | 0.71 | 5414 |
| weighted avg | 0.81 | 0.79 | 0.79 | 5414 |

**Table -1:** Experimental results

The below graph represents multi-class ROC curve (receiver operating characteristic curve) showing the performance of the classification model at different thresholds.

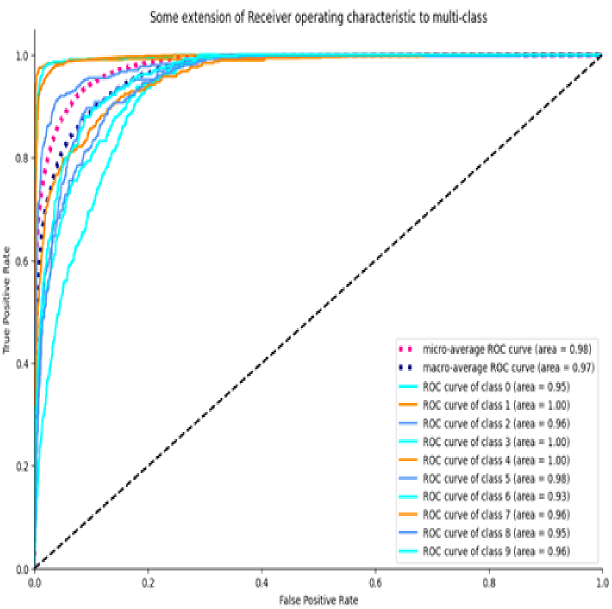


**Fig -4:** Multi-class ROC curve

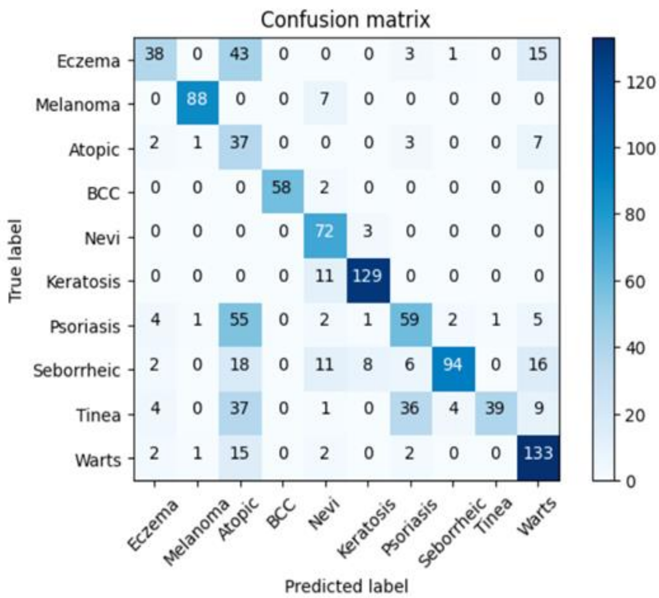


**Fig -5:** Confusion matrix

## V. CONCLUSION

This paper presents a pioneering AI-based tool designed for the preliminary diagnosis of dermatological manifestations, incorporating a user-friendly interface and advanced technological components. The system offers users the choice between uploading a photo or capturing a live image, streamlining the diagnostic process for skin conditions. Leveraging a Convolutional Neural Network (CNN) model with the MobileNet (v2) architecture comprising 12 layers, our system excels in accurate disease detection, providing users with concise disease descriptions.

Moreover, the tool goes beyond mere identification, offering users the option to explore further information or access home remedies for the predicted condition. The language customization feature enhances accessibility, enabling users to comprehend detailed disease descriptions in their preferred language. By seamlessly integrating technology and healthcare, our AI-based system addresses the need for efficient and user-centric dermatological diagnostics, marking a significant step towards empowering individuals with accessible and informative tools for preliminary skin health assessments.

## REFERENCES

[1] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.

[2] Haenssle, H. A., Fink, C., Schneiderbauer, R., Toberer, F., Buhl, T., Blum, A., ... & Thomas, L. (2018). Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Annals of oncology, 29(8), 1836-1842.

[3] Tschandl, P., Rosendahl, C., & Kittler, H. (2019). The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Scientific data, 5(1), 1-8.

[4] Liu, S., Song, W., Zhang, L., Zhao, X., Pu, J., Zhang, Y., & Gao, W. (2019). A deep learning-based method for skin lesion segmentation in dermoscopy images. Frontiers in Genetics, 10, 1143.

[5] Menegola, A., Tavares, J. M. R., & Fornaciali, M. (2020).A comprehensive review of technologies and methods for automated diagnosis of skin lesions. Frontiers in Robotics and AI, 7, 24.

[6] American Institute for Cancer Research. Skin Cancer Statistics1186 Melanoma of the Skin is the 19th Most Common Cancer 1187 Worldwide. Accessed: Aug. 10, 2020. [Online]. Available: 1188 https://www.wcrf.org/dietandcancer/cancer-trends/skin-cancer-statistics 1189 .

[7] WHO Cancer Today. Skin Melanoma Heatmap of the World in 2020. 1190 Accessed: May 11, 2021. [Online]. Available: https://gco.iarc.fr/

[8] R. L. Siegel, K. D. Miller, H. E. Fuchs, and A. Jemal, ‘‘Cancer statistics, 1197 2021,’’ CA, Cancer J. Clinicians, vol. 71, no. 1, pp. 7–33, Jan. 2021. 1198.

[9] G. A. Holmes, J. M. Vassantachart, B. A. Limone, M. Zumwalt, 1199 J. Hirokane, and E. S. Jacob, ‘‘Using dermoscopy to identify melanoma 1200 and improve diagnostic discrimination,’’ Federal Practitioner, vol. 35, 1201 no. 4, p. S39, 2018.