# Adaptive dermascopy application using machine learning

*Alavala* Maneesha[1*], *Kondam* Anusha[1], *Bjd* Kalyani[1]

[1]Department of Computer Science and Engineering, Institute of Aeronautical Engineering, Hyderabad.

**Abstract.** Skin cancer is the most lethal because skin cells develop abnormally. Finding skin cancer early is very important and may help stop some kinds of skin cancer, like melanoma and focal cell carcinoma. Early detection and classification of skin cancer are difficult and costly. Recurrent networks and ConvNets can automatically extract complex data. This paper proposes to use a handmade features-based multi-layer perceptron and a cascaded ensembled network to upgrade ConvNet models. This convolutional neural network model detects non-handmade picture qualities and generates features like color moments and material properties. With ensembled DL, accuracy increased from 85.3% with convolutional neural networks to 98.3%.

**Keywords** – Dermatology, skin lesion classification, color moments, texture features, deep learning, convolution neural network.

## 1 Introduction

Skin is the biggest bodily layer, covering 20 square feet. It covers the whole body, and its breadth varies greatly between the sexes and between the young and the elderly. The average forearm skin thickness is 1.26 mm for women and 1.3 mm for males. The body is protected from heat, mechanical harm, and direct injury by the skin. Intercellular lipids prevent us from losing water, and it also protects us from pathogens and the elements. Skin cancer diagnoses have increased in recent decades. Survival requires early and frequent skin cancer detection. A lot of cases, though, are not found until they are already very far along, which lowers the chances of survival.

A computer-based diagnosis (CBD) method that automatically sorts microscopic pictures of the skin into groups is an interesting way to find problems early [6]. CBD is basically a method that helps doctors make decisions by looking at medical images. CBD is used to give

* Corresponding author: maneesha2720@gmail.com

doctors more knowledge, but they are the ones who make the right decision. Its main goal is to make doctors better at diagnosing by lowering the number of false negatives that come from observing control and differences between and within observers. Most CBD systems use one of two main types of method. Locating malignancies is the initial step. The next stage is to measure unusual patterns' observable characteristics.

There are three main parts that make up a computer-based monitoring system. The first is an image processing and analysis system that finds the best lesions and worrying patterns to enhance and eradicate. The second step is to measure the pigments' size, color, structure, shape, and contrast, among other things. Finding features that can reliably tell the difference between a tumor and other common physical structures is very important. Last is feature processing, which utilizes the second step's data to distinguish problematic and normal patterns or group skin lesions.

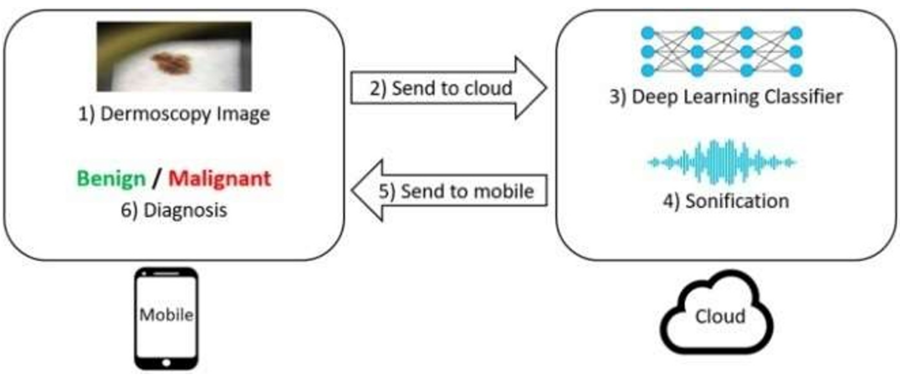


**Fig. 1.** Example figure

Color is one of the most important things to pull out of any item labeling system. One of the most important ways to tell the difference between normal and dangerous melanocytic tumors is by their color. The ABCD dermoscopic idea says that most dangerous melanomas can be spotted by the growth of six scary colors. In terms of histopathology, these scary colors show that melanin is present in the lower layers of the epidermis and dermis [39]. The color histogram has been used in a lot of different projects. The correctness of the color chart is good enough. It does, however, have noise and bad spatial spread.

Color moments are a way to get around the limitations of the color histogram. This shows color photographs using RGB bands. For every channel, determine the mean, standard deviation, skewness, and kurtosis. Thus, a picture has 12 moments—four each channel.

## 2 Literature Survey

### 2.1 Non melanoma skin cancer pathogenesis overview:

Skin cancer that is not melanoma is the most common type in people. We still do not fully understand how skin cancer starts. Several studies, on the other hand, have been done to better understand the paths that lead to cancer. (2)
Methods: New study has focused on basal cell carcinomas, squamous cell carcinomas, and actinic keratosis causing non-melanoma skin cancer. (3) Numerous investigations have shown that non-melanoma skin cancer is caused by genetic and molecular changes. Gene and chemical alterations, compromised immune systems, and UV radiation cause non-melanoma skin cancer. (4) Genetic and molecular alterations are involved in skin cancer development, according to various studies. Having a lot of knowledge on what causes non-melanoma skin cancer makes it simpler to prevent it. Our study focused on molecular and genetic variables and examined various non-melanoma skin cancer factors in depth, unlike others.

### 2.2 Skin cancer classification using convolutional neural networks: Systematic review:

Contemporary convolutional neural network (CNN) algorithms are just as capable as clinicians at identifying photos of skin cancer. Downloading applications to phones might allow patients to acquire a speedy and life-saving diagnosis outside the hospital. We don't know of any new research in this area. This study is the first comprehensive evaluation of CNN-classified skin tumor studies. For present, we exclusively consider skin disease predictions. CNNs are solely used to segregate or group dermoscopic patterns, hence they are not examined here. This research investigates why it's difficult to compare approaches and what issues need to be addressed.
It works: They conducted searches in the English-language literature databases PubMed, Google Scholar, Medline, ScienceDirect, and Web of Science to find original research articles and systematic reviews.. This review exclusively examines excellent scientific method publications. CNNs grouped skin cancers in 13 trials. There are three major approaches to group categorization systems. The most frequent and successful approaches involve a CNN trained on a huge dataset and tweaked to recognize skin cancers. These strategies are suitable for limited datasets.
In conclusion, CNNs are effective skin lesion predictors. Some sorting algorithms employ private data for testing and training, making comparisons difficult. Future research should utilize open standards and explicitly disclose training methodologies for comparison.

### 2.3 Human–computer collaboration for skin cancer recognition:

Telemedicine is growing and medical artificial intelligence (AI) is improving, therefore we need to weigh the merits and drawbacks of employing AI to improve treatment. This research uses recent advances in image-based AI for skin cancer identification to examine how alternative methods of conveying AI-based aid affect clinical expertise and a variety of clinical procedures. High-quality AI-based clinical decision-making enhances diagnosis accuracy more than AI or physicians alone. The least-experienced nurses benefit most from AI. In mobile technology, AI-based multiclass odds outperformed CBIR versions. Second views and medical care models benefited from AI. Poor AI may confound even

professionals in medicine. We also heard about the advantages of high-quality AI for non-expert therapists.
Finally, we demonstrate how AI class-activation maps might improve diagnosis. Our technique and findings pave the way for future research in a variety of image-based examinations to enhance clinical practice between humans and computers.

### 2.4 Management of primary skin cancer during a pandemic: Multidisciplinary recommendations:

During the COVID-19 pandemic, doctors and patients should work together to assess the advantages and disadvantages of starting treatment for localised skin cancer as soon as possible. People who have problems with COVID19 are usually older, have weak immune systems, and have diabetes, cancer, or heart disease. Having more than one of these conditions is linked to worse results. Physicians must assess COVID19 risks against the possibility of poorer cancer outcomes if therapy is delayed. The writers looked at available data on the chances of COVID19 issues and death based on age and other health problems. They also looked at the research on how delays in treatment affect cancer results.
Also, with help from experts from 11 different institutions, they have put together joint guidelines for when to start local treatment for skin cancers in their early stages during this outbreak. The writers suggest that people with Merkel cell cancer should get treatment first, but patients with good T1 disease who are more likely to have COVID19 problems might be given a short break. If there is no apparent illness after biopsy, T0 to T1 melanoma patients should wait three months before starting therapy. If biopsy boundaries are negative, T2 tumor therapy might be delayed for three months. For people with Brigham and Women's Hospital T1 to T2a cutaneous squamous cell carcinoma, treatment can be put off for two to three months unless the tumor is growing quickly, there are symptoms, or the patient's immune system is weak. Treatment for T2b tumors should be given first, but a one- to two-month delay probably won't make disease-specific mortality worse. Patients with in situ squamous cell carcinoma or basal cell carcinoma may not need therapy for three months, unless they are extremely ill.

### 2.5 Development of mobile skin cancer detection using faster R-CNN and MobileNet v2 model:

Cellphone cameras might be used to diagnose cancer at the point of care. Smartphones may be programmed to detect skin cancer characteristics for early detection. Convolution neural networks (CNNs) are used to classify diseases.
However, the CNN approach requires a powerful computer with plenty of memory, which is difficult on a smartphone. For an Android skin cancer app, this study uses MobileNet v2 and Faster R-CNN algorithms. The suggested patterns were trained to identify targets for melanoma and actinic keratosis skin cancer. The 600 photos were separated into melanoma and actinic keratosis categories. Age, gender, or any other factor was disregarded.
In this work, Android software was built to detect skin cancer using smartphone cameras. The sophisticated screening techniques were MobileNet v2 and Faster R-CNN. Our research

tested the Android camera and Jupyter notebook. On Jupyter, MobileNet v2 outperformed faster R-CNN, but not by much on a smartphone.

## 3 Existing System

Existing solutions for skin disease diagnosis include manual examination by dermatologists and computer vision-based tools.

1. **Manual examination:** To identify skin conditions, dermatologists rely on their training and visual inspection. This approach, however, is random and liable to change depending on the knowledge and experience of the user. If the dermatologist is unfamiliar with a problem, it could result in a delayed or incorrect diagnosis.

2. **Computer vision-based tools:** To help with diagnosis, these technologies employ algorithms to analyze photos of skin lesions. They frequently fall short of human dermatologists in terms of accuracy and dependability though. They might have trouble with difficult situations or uncommon diseases.

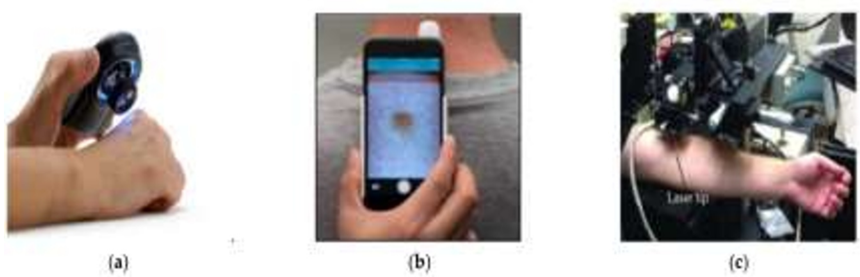


**Fig. 2.** Existing skin disease devices: (a) dermoscopy; (b) dermalite; (c) laser microscopy.

Figure 2a depicts a dermoscopy tool that is frequently used to diagnose melanoma cancer in developed nations. It has proven effective in identifying various skin disorders like cicatricial alopecia, lichen planus, and psoriasis. Dermoscopy makes subsurface skin structures and subtle clinical patterns of skin lesions that are generally invisible to the naked eye apparent. However, when utilizing this tool, a medical practitioner must determine the severity and state of the disease.

Figure 2b displays the derma lite gadget, a handy smartphone attachment for dermoscopy. It makes it possible to take images of moles or other skin lesions that have been greatly magnified and sent to dermatologists for accurate evaluation and diagnosis.

Figure 2c depicts a microscope tool created by Stanford researchers that can identify illnesses, such as skin cancer, and carry out precise surgery (without breaking the skin). However, because it is more expensive, slower, larger, and less accurate than other imaging technologies, laser-based imaging equipment is often not meant for mass use.

### 3.1 Drawbacks

1. It is costly and difficult to identify and classify skin malignant growths at an early stage.
2. Examples of deep learning architectures that have been built in the past and have proven to be effective for non-handcrafted complicated feature extraction are recurrent networks and convolutional neural networks (ConvNets).

Both manual examination and computer vision-based tools can be time-consuming, leading to longer waiting times for patients and delayed treatment.

They also do not adapt or improve over time without significant updates or retraining. As a result, more sophisticated and perceptive diagnostic techniques—like the suggested federated machine learning-based skin disease model—are required.

## 4 Methodology

Skin cancer is the deadliest type of cancer because it is caused by skin cells growing in a strange way. Finding skin cancer early is very important and may help stop some kinds of skin cancer, like melanoma and focal cell carcinoma. It is hard and expensive to find skin cancer early and put it into the right category. Recurrent networks and CNN are two types of DL designs that have already been made and shown to be good at automatically extracting complex features.

### 4.1 Disadvantages

1. It is hard to find and describe skin cancer in its early stages and costs a lot of money.
2. Structures for DL, like recurrent networks and convolutional neural networks (ConvNets), have already been made and shown to be good at automatically extracting complex traits.

The aim of this research is to create a computerized system for melanoma lesion identification that physicians may use to assist them in selecting the appropriate kind of melanoma for treatment. This study suggests a way to classify things and a way to combine features by using a ConvNet model along with custom features made by hand as a cascaded ensembled model.

### 4.2 Advantages

1. Effectiveness of ConvNet models, a cascaded ensemble network combining ConvNet and bespoke features-based multi-layer perceptron's.
2. The ensemble DL model improves accuracy.

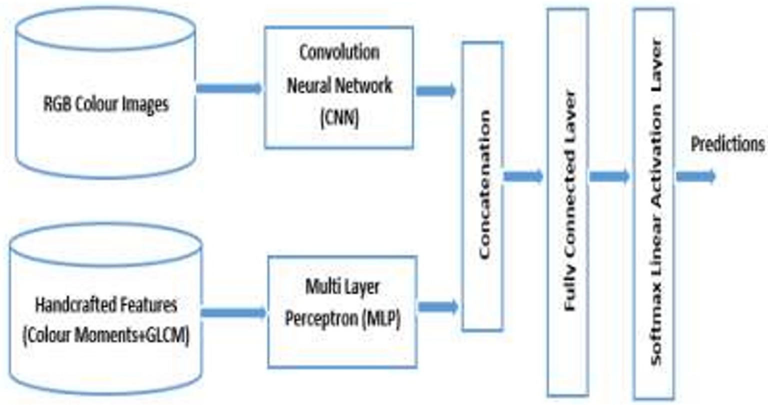


**Fig.3.** System architecture

### 4.3 Modules

The following parts were made so that the above job could be completed.

- **Data exploration:** We will use this tool to add data to the system.
- **Processing:** This part is where we will read data to process it.
- **Splitting data into train & test:** This module will split data into train and test.
- • SVM, Random Forest, MLP, Decision Tree, Voting Classifier, VGG16, MobileNet, CNN, Cascaded Torch by CNN. Calculated algorithm accuracy
- **User signup and login:** If you use this feature, you will have to register and log in.
- **User input:** Prediction input will happen when this module is used.
- **Prediction:** the end number that was predicted will be shown.

## 5 Implementation

### 5.1 Dataset

The lowest number of samples (239 for class 5) and maximum number of samples (12,875 for class 1) correspond to the significantly unequal classes. Furthermore, 4522, 12,875, 3323, 867, 2624, 239, 253, and 628 samples were provided for each class in classes 0, 1, 2, 3, 4, 5, 6, and 7. This issue of class imbalance may lead to overfitting. In order to balance the number of classes in each class, picture augmentation techniques such as image flipping, random cropping, random scaling, center zooming, and adjusting brightness and sharpness are employed to address the overfitting problem. Using appropriate options like Python libraries are also used to increase the sample size of each class image. To lower the computational complexity, the image pixel intensity values are additionally normalised from 0 to 255 to 0 to 1. In 2019 International Skin Imaging Collaboration (ISIC), the skin disease (https://challenge2019.isic-archive.com/) dataset contains imbalanced classes. The fact that the samples in the classes have a lot in common adds to the complexity of this dataset.

25,331 dermoscopy image samples total from nine classes (melanoma (MEL), melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis (AK), benign keratosis (BKL), dermatofibroma (DF), vascular lesion (VASC), squamous cell carcinoma (SSC), and unknown) make up the dataset. With picture examples unrelated to the other eight class types, class UKN is the ninth class in the ISIC 2019 dataset. This helps make the established model more broadly applicable.


**Fig. 4.** Image samples from ISIC (International Skin Imaging Collaboration) dataset; (4a) Melanoma (MEL ); (4b) Melanocvic nevus; (4c) basal cell carcinoma.

### 5.2 Algorithms

1. **Voting Classifier:** Some ML estimators are voting classifiers. It trains numerous base models or estimators and predicts using their outputs. Aggregating criteria may influence estimate outcome voting.
2. **CNN:** CNNs are DL network designs used for image recognition and pixel management. CNNs are the greatest DL neural networks for discovering and identifying items.
3. **SVM:** SVM is a guided ML method for classification and regression. While called recurrence issues, they perform better in groups. SVM separates input points into identifiable groups by finding a hyperplane in N-dimensional space.
4. **Decision tree:** A DT is a type of graph that uses branches to show all the possible outcomes of a certain input. You can draw decision trees by hand or use a drawing program or specialized software to make them. Decision trees may guide a group's decision-making.
5. **Random forest**: For regression as well as classification, random forest is a popular supervised machine learning technique. It builds decision trees using numerous cases, classifying by majority vote and regressing by average.
6. **MLP:** A multilayer perceptron (MLP) is an add-on for a feed-forward neural network. Here we are taking three layers which are the input layer, the output layer, and the secret layer. The input layer is what gets the information that needs to be handled.
7. **VGG16:** With a 92.7% success rate, VGG16 can sort 1000 pictures into 1000 different groups based on how well it can identify objects. This is a popular way to sort pictures into groups, and it works well with transfer learning.
8. **MOBILENET**: In the network model MobileNet, depth wise separable convolution is its foundation. Its depth wise separable convolution has point and depth wise convolution.

## 6 Experimental Results


**Fig. 5.** Home screen

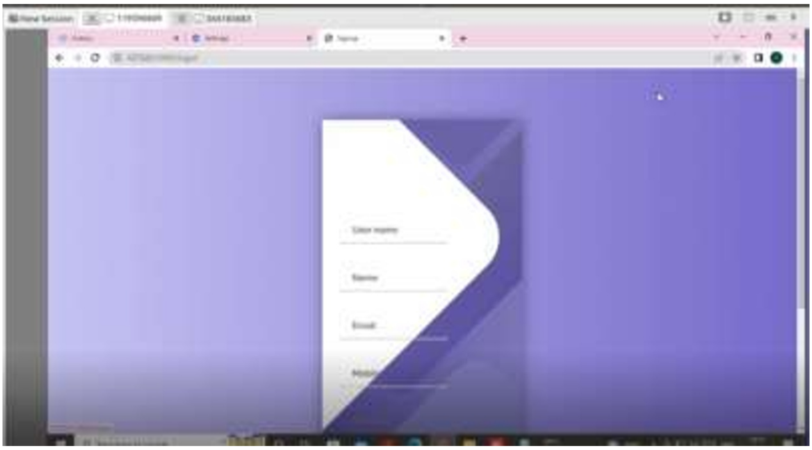

**Fig. 6.** User signup

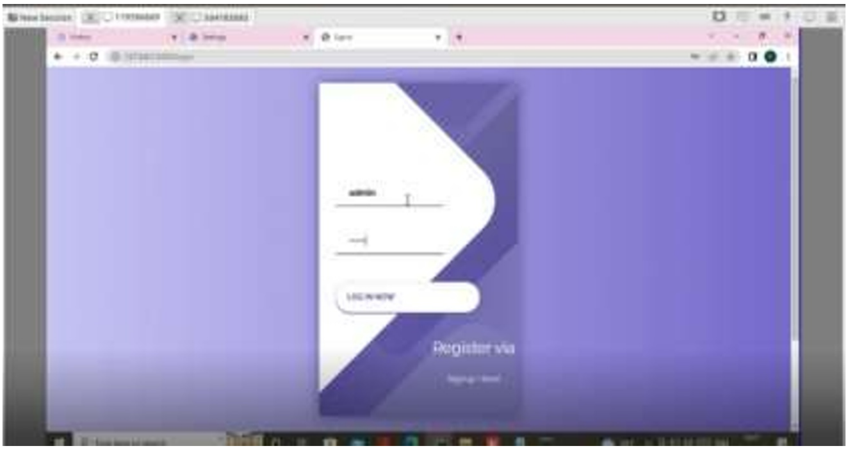


**Fig. 7.** User sign in

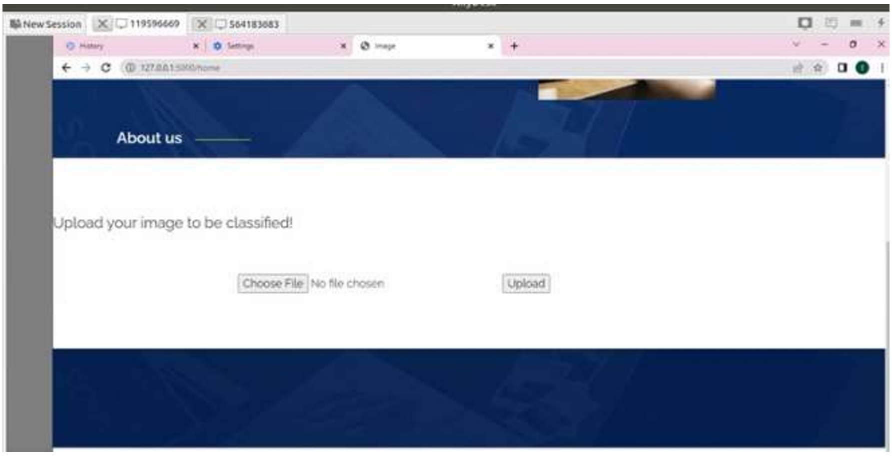


**Fig. 8.** Main screen

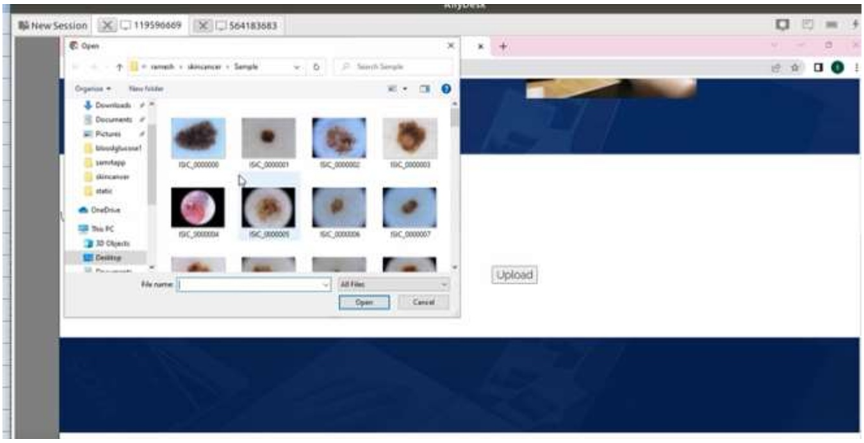


**Fig. 9.** User input

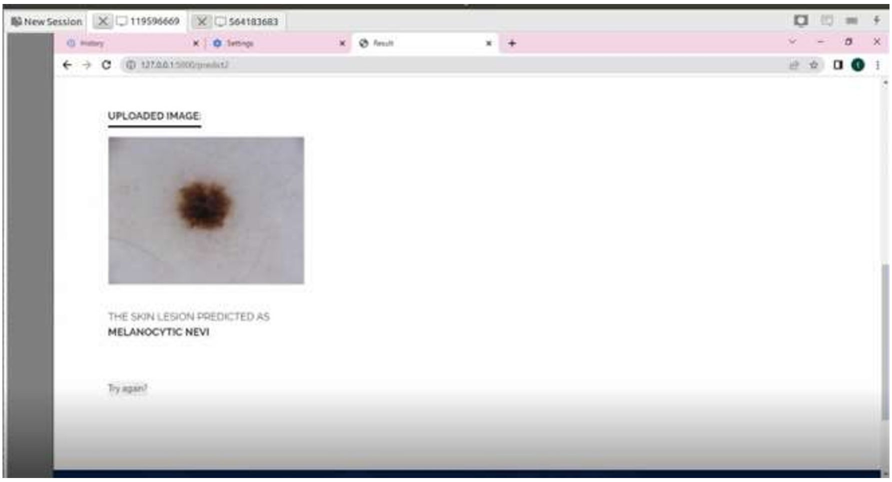


**Fig. 10.** Prediction result

## 7 Conclusion

Based on existing DL models, skin lesions may be classified successfully. We combine the finest of hand-crafted feature extraction approaches with DL models to produce a cascaded model. Combining Deep ConvNets' capacity to learn new features with hand-made characteristics like color moments and texture features yields reliable skin disease photo classification.

This research uses the cascaded ensembled DL model. The exercise shows that our model outperforms ConvNet. Handcrafted elements are being integrated with clinical factors including location, sex, age, burns, itching, and medical history to enhance the model.

## References

1. D. Didona, G. Paolino, U. Bottoni, and C. Cantisani, ''Non melanoma skin cancer pathogenesis overview,'' Biomedicines, vol. 6, no. 1, p. 6, Jan. 2018.
2. T. J. Brinker, A. Hekler, J. S. Utikal, N. Grabe, D. Schadendorf, J. Klode, C. Berking, T. Steeb, A. H. Enk, and C. von Kalle, ''Skin cancer classification using convolutional neural networks: Systematic review,'' J. Med. Internet Res., vol. 20, no. 10, Oct. 2018, Art. no. e11936.
3. P. Tschandl, C. Rinner, Z. Apalla, G. Argenziano, N. Codella, A. Halpern, M. Janda, A. Lallas, C. Longo, J. Malvehy, J. Paoli, S. Puig, C. Rosendahl, H. Peter Soyer, I. Zalaudek, and H. Kittle, ''Human–computer collaboration for skin cancer recognition,'' Nature Med. vol. 26, no. 8, pp. 1229–1234, 2020.
4. B. C. Baumann, K. M. MacArthur, J. D. Brewer, W. M. Mendenhall, C. A. Barker, J. R. Etzkorn, N. J. Jellinek, J. F. Scott, H. A. Gay, J. C. Baumann, F. A. Manian, P. M. Devlin, J. M. Michalski, N. Y. Lee, W. L. Thorstad, L. D. Wilson, C. A. Perez, and C. J. Miller, ''Management of primary skin cancer during a pandemic: Multidisciplinary recommendations,'' Cancer, vol. 126, no. 17, pp. 3900–3906, Sep. 2020.
5. J. Höhn et al., ''Combining CNN-based histologic whole slide image analysis and patient data to improve skin cancer classification,'' Eur. J. Cancer, vol. 149, pp. 94–101, May 2021.
6. C. A. Hartanto and A. Wibowo, ''Development of mobile skin cancer detection using faster R-CNN and MobileNet v2 model,'' in Proc. 7th Int. Conf. Inf. Technol., Comput., Electr. Eng. (ICITACEE), Sep. 2020, pp. 58–63.
7. M. A. Kassem, K. M. Hosny, R. Damaševičius, and M. M. Eltoukhy, ''Machine learning and DL methods for skin lesion classification and diagnosis: A systematic review,'' Diagnostics, vol. 11, no. 8, p. 1390, Jul. 2021.
8. O. O. Abayomi-Alli, R. Damaševičius, S. Misra, R. Maskeliunas, and A. Abayomi-Alli, ''Malignant skin melanoma detection using image augmentation by oversampling in nonlinear lower-dimensional embedding manifold,'' TURKISH J. Electr. Eng. Comput. Sci., vol. 29, nos. SI–1, pp. 2600–2614, Oct. 2021.
9. T. C. Pham, V. D. Hoang, C. T. Tran, M. S. K. Luu, D. A. Mai, A. Doucet, and C. M. Luong, ''Improving binary skin cancer classification based on best model selection method combined with optimizing full connected layers of deep CNN,'' in Proc. Int. Conf. Multimedia Anal. Pattern Recognit. (MAPR), Oct. 2020, pp. 1–6.

10. N. Hameed, A. Ruskin, K. Abu Hassan, and M. A. Hossain, ‘‘A comprehensive survey on image-based computer aided diagnosis systems for skin cancer,’’ in Proc. 10th Int. Conf. Softw., Knowl., Inf. Manage. Appl. (SKIMA), 2016, pp. 205–214.
11. D. Didona, G. Paolino, U. Bottoni, and C. Cantisani, ‘‘Non melanoma skin cancer pathogenesis overview,’’ Biomedicines, vol. 6, no. 1, p. 6, Jan. 2018.
12. T. J. Brinker, A. Hekler, J. S. Utikal, N. Grabe, D. Schadendorf, J. Klode, C. Berking, T. Steeb, A. H. Enk, and C. von Kalle, ‘‘Skin cancer classification using convolutional neural networks: Systematic review,’’ J. Med. Internet Res., vol. 20, no. 10, Oct. 2018, Art. no. e11936.
13. P. Tschandl, C. Rinner, Z. Apalla, G. Argenziano, N. Codella, A. Halpern, M. Janda, A. Lallas, C. Longo, J. Malvehy, J. Paoli, S. Puig, C. Rosendahl, H. Peter Soyer, I. Zalaudek, and H. Kittle, ‘‘Human–computer collaboration for skin cancer recognition,’’ Nature Med. vol. 26, no. 8, pp. 1229–1234, 2020.
14. B. C. Baumann, K. M. MacArthur, J. D. Brewer, W. M. Mendenhall, C. A. Barker, J. R. Etzkorn, N. J. Jellinek, J. F. Scott, H. A. Gay, J. C. Baumann, F. A. Manian, P. M. Devlin, J. M. Michalski, N. Y. Lee, W. L. Thorstad, L. D. Wilson, C. A. Perez, and C. J. Miller, ‘‘Management of primary skin cancer during a pandemic: Multidisciplinary recommendations,’’ Cancer, vol. 126, no. 17, pp. 3900–3906, Sep. 2020.
15. J. Höhn et al., ‘‘Combining CNN-based histologic whole slide image analysis and patient data to improve skin cancer classification,’’ Eur. J. Cancer, vol. 149, pp. 94–101, May 2021.