Skin Lesion Detection and Classification

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*Abstract*— This project aims to develop an automated system for classifying skin lesions, such as moles and melanomas, using deep learning. Utilizing the HAM10000 and ISIC2018 datasets, the system leverages TensorFlow for model development and Flask for API creation, integrating with a Flutter-based mobile app. Key techniques include image preprocessing, resizing, and data augmentation to improve model accuracy. The InceptionResNet model, trained on these images, achieves 96.13% accuracy. The project also uses Colab for GPU acceleration and Git for version control. Future enhancements will focus on refining accuracy, adding real-time detection, and ensuring medical compliance, ultimately aiding healthcare professionals in diagnosing skin lesions accurately and timely.

***Keywords—Skin,Lesions, Melanoma,Cancer,Dermoscopics,***

# **Introduction**

The skin is the broadest organ in the body which protects the body against the heat, light, and infection. It also helps to control the body temperature and to store the fat and the water. One of the most important problems of skin in the body is its infection risk to skin cancer.

Melanoma is the most malignant and most serious type of skin cancer and is the reason for most deaths from skin cancer. The underlying cause of melanoma is unknown . But several factors, including genetic factors, ultraviolet radiation, and environmental contact are involved in causing the disease.[3]

Given these challenges, there is a critical need for an automated system that can quickly and accurately classify different types of skin lesions. This application encourages people to check their skin lesions promptly, helping to detect potential issues before the disease becomes more serious. Such a system will assist healthcare providers by offering consistent and reliable assessments, improving diagnostic efficiency, and ensuring timely and appropriate care for patients.

# **related work**

|  |  |  |  |
| --- | --- | --- | --- |
| Paper | Methodologies | Datasets | Evaluation |
| Skin lesion classification of dermoscopic images using machine learning and convolutional neural network “2022” | Decision Tree, Random Forest , SVM, KNN, CNN | HAM10000 | DT : 68%,  RF : 87% |
| Skin Lesion Classification on Imbalanced Data Using Deep Learning with Soft Attention”2022" | DenseNet201, InceptionResNetV2, ResNet50, VGG16,  Upsizing: data augmentation | HAM10000 | 86% combination of MobileNetV3,Soft-Attention  92% InceptionResNetV2 with Soft-Attention |
| Detection of Skin Cancer Based on Skin Lesion Images Using Deep Learning “Health Care 2022”.[10] | CNN, Resnet50, InceptionV3, Inception Resnet, ESRGAN, Validation patience, Upsizing: data augmentation | HAM10000  ISIC2018 | the Inception  model had an  overall accuracy  rate of 85.7% |
| Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques”2020” | RCNN along with  FKM, Polesel,  Ramponi, Mathews | ISIC-2016, ISIC-  2017, and PH2 | 0.945, 0.963, and  0.971 respectively  with datasets |
| State-of-the-art machine learning techniques for melanoma skin cancer detection and classification: a comprehensive review “2023”.[12] | DCNN, AlexNet,  VGG16, FCNs  based on VGG16  and GoogleNet,  Deep RCNN and  Fuzzy C-Mean  Clustering,  DenseNet with  IcNR, Optimized  CNN,  Upsizing: data augmentation | PH2 , ISIC 2017,ISBI 2016, ISBI 2017 , ISBI 2017, ISIC Archive | Optimized CNN :  93%  DCNN : 95%  LDA with CNN :  85% |
| Skin Cancer Detection Using Deep Learning—A Review “2023”  [8] | AlexNet, VGG,  ResNet,  DenseNet,  MobileNet,  Upsizing: data augmentation | HAM1000,  PH2,ISIC”2016 to 2020”,  Atlas of Dermoscopy,  Dermofit,  BCN20000,  PAD-UFES-20 | VGG-16 achieving the best accuracy of 88% Xception achieving the  highest accuracy of 90.48% |
| The Development of a Skin Cancer Classification System for Pigmented Skin Lesions Using Deep Learning ”2020”. | VGG-16,stochastic gradient descent. data augmentation | approximately 120,000 clinical images taken from 2001 to 2017 at the Department Dermatologic Oncology in the National Cancer Center Hospital, they extracted 5846 clinical images of brown to black pigmented skin lesions from 3551 patients. “Not Accessible” | 86.2% for the FRCNN. |
| Skin Lesions Classification Based on Deep Learning Approach “2020”. | VGG16, Inception\_V3, ResNet-50. | ISIC Archive Dataset | 85.3%,84.3% and 81.7 respectively with methodologies. |
| Classification of Skin Cancer Images using Convolutional Neural Networks”2022” | DenseNet,Resnt,  XceptionNet,  MobileNet,  Augmentation | Skin Cancer:  Malignant vs.  Benign | DenseNet : 86%  Resnet : 86%  XceptionNet: 82%  MobileNet : 80% |
| Soft-Attention Improves Skin Cancer Classification Performance”2021” | Deep CNN,  Deep CNN with soft-Attention  Up sizing: Data augmentation | ISIIC 2017  HAM 10000 | HAM10000 + CNN + Soft :  93.7%  ISIC2017 + CNN + Soft :  91.6% |

Table 1 Related Work

**Detection of Skin Cancer Based on Skin Lesion Images Using Deep Learning “Health Care 2022”**Walaa Gouda. [10] introduced a skin cancer detection system utilizing CNN, Resnet50, InceptionV3, Inception Resnet, and ESRGAN. The study included validation patience and data augmentation for enhancing the dataset. The HAM10000 and ISIC2018 datasets were used, with the Inception model achieving an overall accuracy rate of 85.7%

**State-of-the-art machine learning techniques for melanoma skin cancer detection and classification: a comprehensive review “2023”**  
Harsh Bhatt. [12] reviewed various state-of-the-art machine learning techniques for melanoma detection and classification, including DCNN, AlexNet, VGG16, FCNs based on VGG16 and GoogleNet, Deep RCNN, Fuzzy C-Mean Clustering, and DenseNet with IcNR. The study also highlighted the effectiveness of optimized CNN and data augmentation techniques. The PH2, ISIC 2017, ISBI 2016, ISBI 2017, and ISIC Archive datasets were used, with optimized CNN achieving 93% accuracy, DCNN 95%, and LDA with CNN 85%.

# **system architecture**

. A diagram of a mobile application

Description automatically generated

1. **Application Layer**

User Interface and communication layer of the application where the end user interacts with the application.

**Mobile Application**

- **User Interaction**: The mobile application provides the interface through which users interact with the system. Users can capture or upload images, submit them for classification, and view the results.

- **Image Capture**: Users can take a photo using the device's camera or select an existing image from the gallery.

- **Sending Data**: Once an image is captured or selected, it is sent to the backend (Mobile App API) for processing.

- **Displaying Results**: After the backend processes the image and returns the classification result, the mobile app displays the result to the user.

1. **Processing Layer**

The “**Mobile App API**” module which is in the application layer- is responsible for the data flow between the three layers and most of their modules.

**Preprocessing**

**- Image Resizing:** Adjusts the dimensions of the image to fit the requirements of the deep learning model

**- Normalization:** Adjusts the pixel values to a standard scale (e.g., values between 0 and 1 or -1 and 1) to improve the model's performance.

**- Data Augmentation:** Applies transformations like rotation, flipping, and cropping to increase thevariability of the training data and improve the model's robustness.

**Feature Extraction**

* **This module** extracts relevant features from the preprocessed image.
* This step reduces the dimensionality of the data and retains essential information needed for classification.

**Load Pre Trained Model**  
**Convolutional Neural Networks:**  The CNNs are extensively utilized in the classification of skin lesion images due to their exceptional performance and remarkable outcomes. CNNs, being a type of multilayer perceptron, form a fully connected network where each neuron is connected to all neurons in the subsequent layer.

These networks employ convolutional operations to extract significant features from the input data.

  They consist of various layers, such as convolutional layers, pooling layers, and fully connected layers.

In the context of skin lesion image classification, the neurons in CNNs possess three dimensions → width, height, and depth.

Additionally, they establish selective connections with a small region of the previous layer.

 Consequently, CNNs have gained immense popularity as highly effective Deep Neutral Network arch have rained in related to skin lesion image classification.

**Classification**

* The model processes the features and produces a classification output.
* The classification result is sent back to the Mobile App API to be returned to the mobile application.

**3. Data Layer**

- includes a **database** that is primarily used to store and retrieve the pretrained model and its weights. This ensures that the model and its associated weights are securely stored and can be accessed efficiently for processing images.

##### **results**

|  |  |  |  |
| --- | --- | --- | --- |
| model | Data | Hyperparameters values | Accuracy |
| SVM | HAM10000 | Kernel = ’linear’, c = 1 | 42% |
| DT | HAM10000 | Max\_depth = 100 | 44% |
| RF | HAM10000 | n\_estimators = 200 | 68% |
| RF | HAM10000 with Data Augmentation | n\_estimators = 200 | 80% |
| CNN | HAM10000 | Learning rate = 0.001  Epochs = 70 | 86% |
| Inception Net | HAM10000 | Learning rate = 0.0001  Epochs = 50  Fine tuning exclude 10 layers | 85% |
| Inception Net | HAM10000 | Learning rate = 0.001  Epochs = 50  Fine tuning exclude 5 layers | 87% |
| Inception Net | HAM10000 with Data Augmentation | Learning rate = 0.001  Epochs = 50  Fine tuning exclude 5 layers | 84% |
| Inception ResNet | HAM10000 | Learning rate = 0.001  Epochs = 70 | 92.3% |
| Inception ResNet | HAM10000 with Data Augmentation | Learning rate = 0.001  Epochs = 70  L2 regularization | 84% |
| Inception ResNet | HAM10000 with Data Augmentation | Learning rate = 0.01  Epochs = 70  Retrain except 30 layers | 94.22% |
| Inception ResNet | HAM10000 with Data Augmentation | Learning rate = 0.01  Epochs = 70  Retrain except 28 layers  - Using Step Decay - Add 2 Dense layers | 96.13% |

Table 2 Results

A graph with different colored bars

Description automatically generated

Dataset

Two datasets are used to train and evaluate the different models implemented in this project. Each of the datasets is explained below, outlining the data format, number of entries, etc. The datasets are: HAM10000 , ISIC2018.

**HAM10000: Dermoscopic Skin Lesion Classification**

**Dataset :**

The HAM10000 dataset is a collection of dermoscopic images designed to train machine learning models for classifying pigmented skin lesions.

**Content:**

* **Images:** 10015 dermoscopic images of pigmented skin lesions acquired from diverse populations and sources.
* **Labels:** Each image is assigned one of seven diagnostic categories:
  + Actinic keratoses and intraepithelial carcinoma (akiec)
  + Basal cell carcinoma (bcc)
  + Benign keratosis-like lesions (bkl)
  + Dermatofibroma (df)
  + Melanoma (mel)
  + Melanocytic nevi (nv)
  + Vascular lesions (vasc)
* **Ground Truth:** Over 50% of lesions have histopathological confirmation. The remaining diagnoses are confirmed through follow-up examination, expert consensus, or in-vivo confocal microscopy.
* A close-up of a pattern of squares

  Description automatically generated**Multi-Image Lesions:** The dataset includes lesions with multiple images linked by a unique identifier (lesion\_id) within the metadata file.

**ISIC2018 :-**

Several skin diseases

Description automatically generated with medium confidenceThe HAM10000 dataset provides 10015 labeled dermoscopic images of pigmented skin lesions for training machine learning models in classification. This dataset, along with the ISIC 2018 challenge that builds upon it, serves as a valuable resource for researchers developing and evaluating automated systems for skin lesion classification, particularly melanoma detection. The ISIC 2018 challenge offered tasks in lesion segmentation, attribute detection, and disease classification, providing ground truth data for evaluation and

##### **conclusion&future work**

**conclusion:**

We utilized the Human Against Machine Dataset (HAM10000) and the International Skin Imagaing Dataset (ISIC2018) for our work. The images were resized to a resolution of 299 x 299. Additionally, we applied data augmentations techniques to improve accuracy. Several machine learning and deep learning models, including SVM , Decision Trees, Random Forest, basic CNN, InceptionNet and InceptionResNet.

Among these models, InceptionResNet yielded the best overall results.

We explored various hyperparameters, optimizers, batch sizes, number of epochs, and activation functions for each mentioned model. Our Flutter mobile application was developed and linked with the model by using Flask API to deploy it on portable mobile devices.

Overall, the results obtained were promising, demonstrating the accurate identification of different types of skin lesions from images. The accuracy achieved by the different models ranged from 42% to 96.13%.

**Future work:**

Future work on this project will focus on making the skin lesion classification model more accurate with higher accuracy and reliable by using advanced techniques and larger datasets. Conducting trials and meeting medical standards will ensure the system works well and is safe in real-world use.

Improving images preprocessing by many steps such as: image segmentation process to remove the background of the image and eliminate noise in the form of hair and air bubbles.

**Adding many features to the application:**

* Connect the user with the best doctors.
* The user has medical record that can be shared with his doctor.
* Using the image processing techniques to take excellent shot affected area of the skin when the area captures a photo.
* Notify the user to do some periodic checkups.

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