Web-based system for Skin Anomaly Classification using Deep Learning

Riya Eliza Shaju
19BDS0061

Objective

The project aims to reduce lines at an emergency room and ease a patient when they encounter an unknown growth on their skin. The user is able to upload an image on a weblink and get results about the disease, possible causes, severity, and can converse with a chatbot regarding symptoms and how quickly they should meet a professional. The model is trained using a transfer learning technique, Mobile net, which is a pre trained model and is deployed on a cloud based service. The website will help the user gauge the severity and is well in line with our fast paced modern world. The users can get an accurate primary diagnosis and will further be directed to meet a specialist. This product can save the patients' waiting time at a hospital and clear emergency rooms, prioritizing more severe cases.

Key words: Deep Learning, Skin disease, Health care, MobileNet

Motivation

The primary cause of cancer in the majority of individuals worldwide is ignoring a new skin development that may be cancerous. Due to a lack of information, ignorance, or just not having the time to wait in long lines to see a dermatologist, this may be the case. This short ignorance can have grave consequences. In order to increase efficiency in detecting these disease, a user friendly system is proposed that is able to give a primitive diagnosis with the click of a button. The user is given statistics about the anomaly and can then gauge the need to meet a professional well in advance. This process take just a few minutes which intron saves the many hours spent at a waiting room in a hospital.

Literature survey

SL. No	Title (Year)	Abstract	Conclusion/ Drawbacks
1.	A Smartphone-Based Skin Disease Classification Using MobileNet CNN (2019)	To construct a skin disease classification system for an Android application, transfer learning was applied to the MobileNet model and the 7 skin diseases. 3,406 photographs in total were gathered by the proponents, and because there are not an equal amount of images in each class, the dataset is deemed to be unbalanced. To further increase the accuracy of the MobileNet, several sampling techniques and	The seven skin illnesses were correctly identified by the research with a 94.4% accuracy rate. In conclusion, various sampling approaches and input data preparation can be investigated in order to improve the model's accuracy. In our investigation, the most accurate results were produced via oversampling and data augmentation.

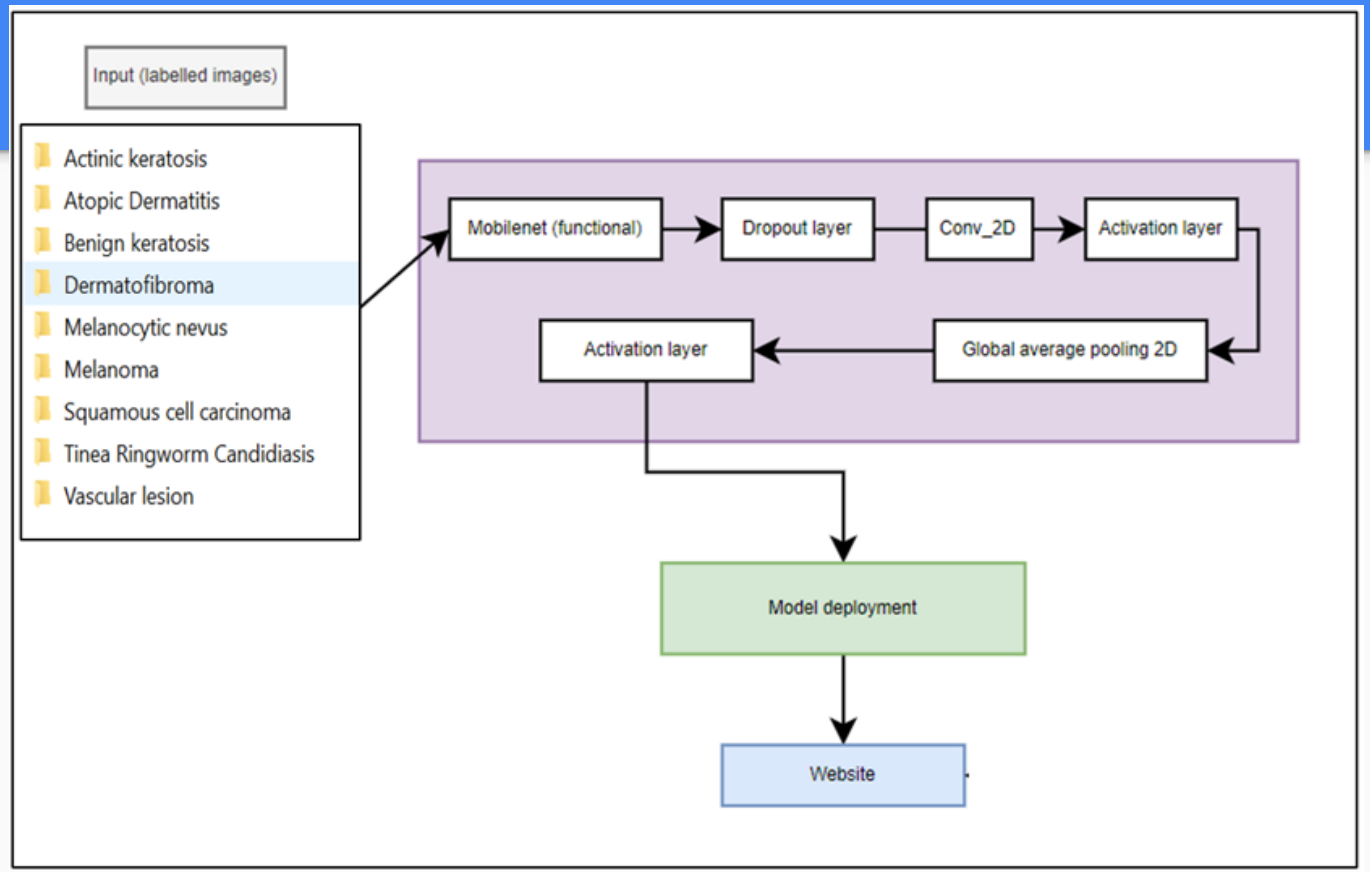
		input data preprocessing were investigated. This model was implemented in the created Android application and provided a 94.4% accuracy by applying oversampling approach and data augmentation on preparing the input data.	
2.	Convolutional Neural Network for Skin Lesion Classification: Understanding the Fundamentals Through Hands-On Learning (2021)	A practical educational exercise that breaks down the steps to train a convolutional neural network using photos of skin lesions connected to several skin cancer classifications. The task can be performed without the need to install any software because it is open-source. We also give a detailed explanation of the algorithm's operations, going over how the computer code's fundamental elements were created before leading the reader through the execution of a practical example that includes visualization and result evaluation.	A potent method for addressing the development of analytical and problem-solving abilities might be to use an interactive, hands-on exercise that replicates a fresh approach in its complexity. Making this technology more accessible will strengthen the partnership between dermatologists and computer scientists as a whole, strengthening their collaborative efforts to advance image-based medical diagnostics.

3.	A Skin Disease Detection System Using CNN Deep Learning Algorithm (2021)	This model separates normal skin from skin with anomalies like pigmentation, rosacea, and acne while also recommending solutions for treating the latter. For this study, 5000 photos were gathered from Dermnet.com and additional outside sources. Transfer learning has been utilized to categorize the skin into one of the four categories by first extracting visual characteristics using a MobileNetV2 model that has been pretrained on more than one million ImageNet photos, and then adding and training a fully connected layer with the dataset obtained.	The created system outlines a practical method for categorizing photos into one of the most prevalent skin illnesses utilizing a transfer learning-based CNN model. The model's outcomes were remarkably comparable to those of skilled dermatologists; the model's recommendations were in line with those of a real dermatologist. It is possible to hypothesize, based on the outcomes of the suggested system, that a transfer learning strategy with data augmentation can produce reliable results.
4.	Automatic skin disease diagnosis using deep learning from clinical image and	Various smartphone cameras were used to capture clinical photos, and patient data was gathered during registration. Prior to training, various data preprocessing and augmentation	Using clinical images and patient clinical information, a smartphone-based automatic diagnosis of five common skin disorders is proposed in this work.

	patient information (2022)	approaches were used to improve the model's performance.	The findings show that the devised approach performs exceptionally well in terms of skin condition diagnostics. The established diagnostic system may be utilized to assist patients, general practitioners, healthcare providers in rural regions, and dermatologists in the diagnosis of skin diseases.
5.	Derm-NN Skin Diseases Detection Using Convolution Neural Network (2020)	Dermatitis hand, eczema hand, eczema subcute, lichen simplex, statis dermatitis, and ulcers are classifications for common skin conditions. In this study, machine learning and picture handling techniques are sandwiched together. CNN uses the image that was created during the picture preparation process to set up the classes.	All things considered, there is a plan to update this framework for the task. After this system is overhauled, people, especially those who are impoverished and reside in remote areas of the country, will soon be able to receive assistance effectively and handle their problems with less effort. The main goal of this project is to break free from the constraints imposed by the framework that has been put in place.

		The preparation information is divided into five categories by the skin gives that were previously discussed. By updating our framework on the dermnet dataset of 500 images of various diseases, they have 73% accuracy. If the other improvements are completed using a larger portion of the dataset, this will turn out to be a fantastic accomplishment.	To take a shot at the picture, the photo handling calculations for background erasing should be used. However, they need to update this system with better calculations to increase accuracy so they can detect any skin problems using only their mobile phone's camera and the internet.

System architecture

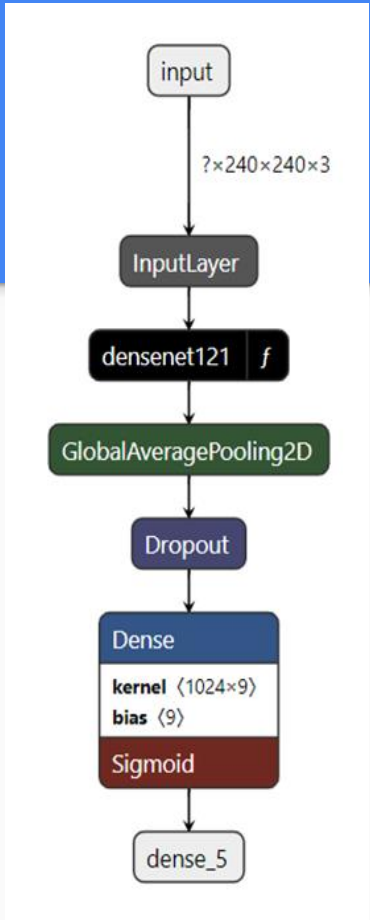


Working Principle

Deep Learning - DenseNet model (self trained on self created dataset)

Layer (type)	Output Shape	Param #
densenet121 (Functional)	(None, 7, 7, 1024)	7037504
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1024)	0
dropout (Dropout)	(None, 1024)	0
dense (Dense)	(None, 9)	9225

Total params: 7,046,729
Trainable params: 6,963,081
Non-trainable params: 83,648



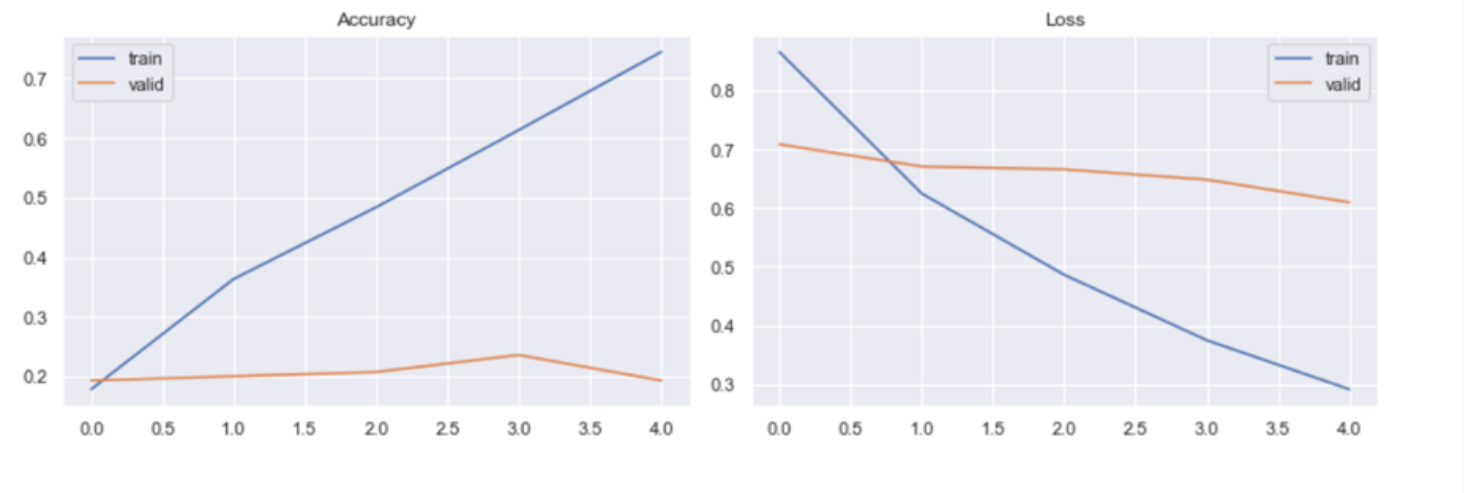
Demonstration

Local IDE - Web app

The front-end of the web-app was created using HTML and CSS, the backend using Python and integration using flask.

Results and analysis

Training of the DenseNet model



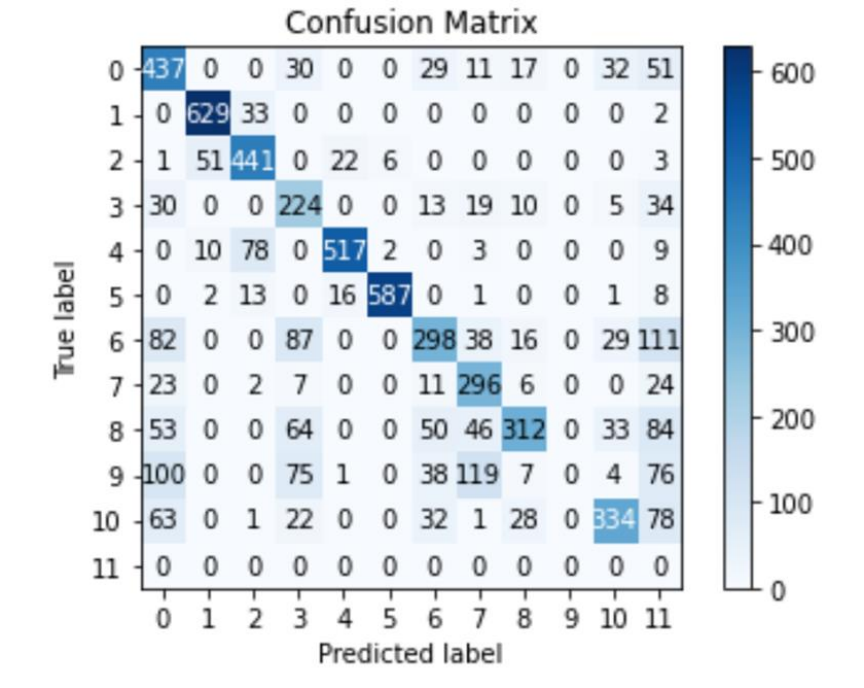
Results and analysis

Predictions using test images:

Training accuracy = 73.0%

Test accuracy = 67.7%

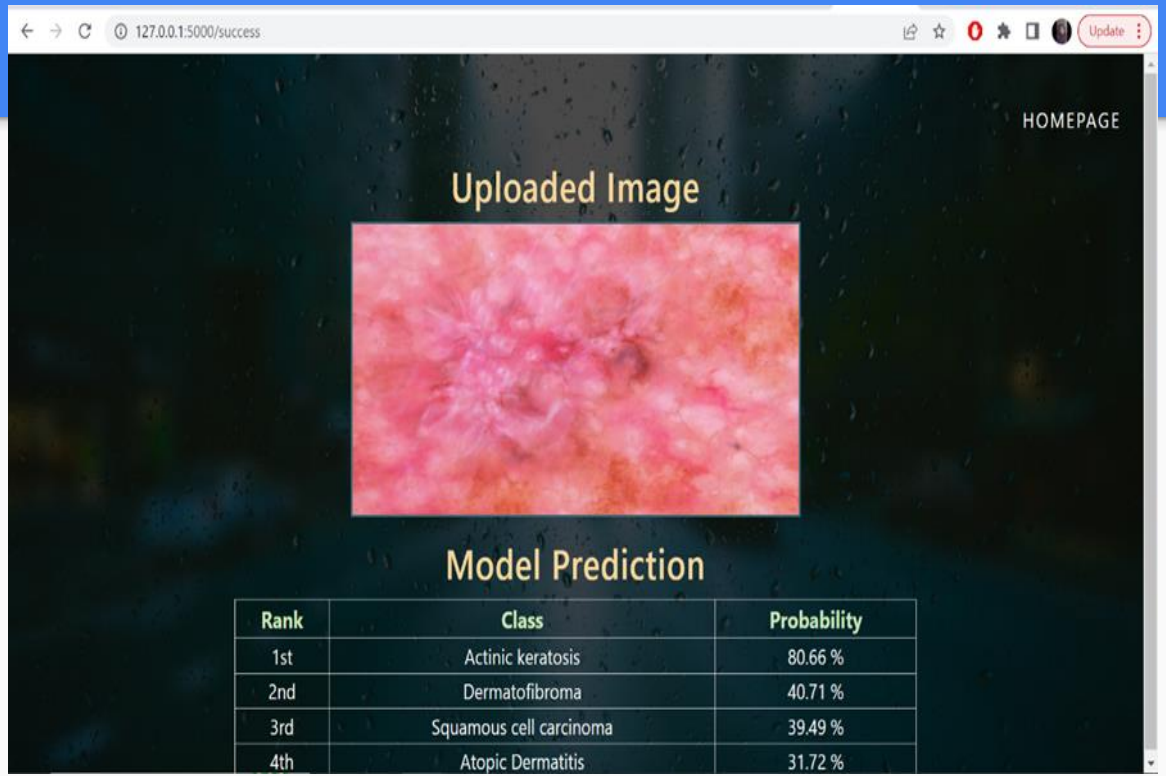
Training loss = 0.25



Web results

Web results predict correctly

with 80%-95% accuracy



Conclusion

The successful implementation of the proposed system has the potential to address several limitations in the current healthcare landscape, including limited access to dermatologists, long waiting times for appointments, and the potential risks associated with delayed diagnosis. By leveraging the power of deep learning algorithms and integrating them into a user-friendly web application, individuals can gain valuable insights into their skin conditions and receive appropriate recommendations for further medical consultation. Furthermore, the project's focus on using pretrained models, optimization techniques, and potential future enhancements such as incorporating text prompts and training with text/NLP can further enhance the accuracy and effectiveness of the system.

Future enhancements

a. Use a Light Pre-trained Model: To address the drawback of model size, future enhancements could involve exploring and implementing lighter pre-trained models that are specifically designed for deployment on mobile or web platforms. These models are optimized for efficiency and can provide comparable accuracy with reduced resource requirements.

b. Increased Accuracy with Text Prompts: Incorporating text prompts along with image inputs can enhance the accuracy of the system. By leveraging natural language processing (NLP) techniques, the system can analyze textual descriptions provided by the users to further refine the diagnosis and provide more accurate results.

c. Training Model with Text/NLP:In addition to image classification, training the model with text or NLP techniques can expand the system's capabilities. This enhancement can enable the system to process textual information related to symptoms, medical history, or additional context, thereby providing more comprehensive

References

Journals:

1. J. Velasco, “A smartphone-based skin disease classification using MobileNet CNN,” *International Journal of Advanced Trends in Computer Science and Engineering*, pp. 2632–2637, 2019.
2. M. Cullell-Dalmau, S. Noé, M. Otero-Viñas, I. Meić, and C. Manzo, “Convolutional neural network for skin lesion classification: Understanding the fundamentals through hands-on learning,” *Frontiers in Medicine*, vol. 8. 2021.
3. Iyer, Aparna, Shraddha Iyer, and Kshitija Hire. "A Skin Disease Detection System Using CNN Deep Learning Algorithm." In *Soft Computing and Signal Processing*, pp. 191-201. Springer, Singapore, 2021
4. K. A. Muhaba, K. Dese, T. M. Aga, F. T. Zewdu, and G. L. Simegn, “Automatic skin disease diagnosis using deep learning from clinical image and patient information,” *Skin Health and Disease*, vol. 2, no. 1, 2021.
5. Rimi, T.A., Sultana, N. and Foysal, M.F.A., 2020. May. Derm-NN: skin diseases detection using convolutional neural network. In *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1205-1209). IEEE.

References (websites)

1. Keras Team. “DenseNet.” *Keras: Deep Learning for Humans*, 20 Feb. 2023, https://keras.io/api/applications/densenet/.

2. Keras Team. *Keras Documentation: MobileNet, MobileNetV2, and MobileNetV3*. keras.io/api/applications/mobilenet.
3. “Coursera | Online Courses and Credentials From Top Educators. Join for Free | Coursera.” *Coursera*, www.coursera.org/learn/image-understanding-tensorflow-gcp/home/week/1.
4. “Coursera | Online Courses and Credentials From Top Educators. Join for Free | Coursera.” *Coursera*, www.coursera.org/learn/feature-engineering/home/week/1.
5. Python Simplified. “Simple Web App With Flask and Heroku - Python GUI for Beginners.” *YouTube*, 25 Sept. 2021, www.youtube.com/watch?v=6plVs_ytIH8.
6. “Skin Lesion Images for Melanoma Classification.” *Kaggle*, 28 May 2020, www.kaggle.com/datasets/andrewmvd/isic-2019.