

Multiclass Derma Detection Using Deep Transfer Learning

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Abstract: *The Multiclass Derma Detection Using Deep Transfer Learning project is aimed at developing a deep learning model that can detect derma on the human body. Acne, Allergy, Tinea Facial is a common skin condition that affects people of all ages and can lead to low self-esteem and depression if left untreated. Early detection and treatment can help prevent scarring and other serious complications. The proposed solution involves using transfer learning, a technique that involves leveraging pre-trained models for a related task to train a new model for a specific task. The pre-trained model will be fine-tuned on a dataset of labelled images to detect acne, allergy, tinea facial on the human body. The model will be trained to classify the severity of acne into three classes: mild, moderate, and severe. The dataset used in this project will be obtained from various sources, including online repositories and dermatology clinics. The dataset will be pre-processed to remove noise and inconsistencies, and the images will be resized to a standardized size. Data augmentation techniques will be used to increase the dataset's size and improve the model's generalization ability.*

Keywords: Machine learning, Deep learning, Neural Network, Convolutional Neural Network, VGG 19, RESNET 50

I. INTRODUCTION

In the medical field, examining skin diseases manually involves dermatologists and healthcare professionals visually inspecting a patient's skin and using their clinical expertise to diagnose and manage various skin conditions. manual examination remains a crucial aspect of dermatology practice.

Clinical Examination: Dermatologists perform a comprehensive clinical examination of the patient's skin. They observe the color, texture, size, shape, and distribution of skin lesions. Factors like symmetry, borders, and presence of scales or crusts are also considered.

Dermatoscopy: Dermatoscopy, also known as dermoscopy or epiluminescence microscopy, involves using a dermatoscope to examine skin lesions in greater detail. Dermatoscopes provide magnified views and enhanced lighting, allowing dermatologists to observe pigment patterns, vascular structures, and other subtle features.

Clinical History: Dermatologists gather information about the patient's medical history, family history, recent changes, and symptoms related to their skin condition. This context helps in making accurate diagnoses.

II. LITERATURE REVIEW

The most common form of the disease in humans is a skin disease. The causes of skin diseases include fungal infections, bacterial infections, viruses, etc. Dermatologists play a crucial role in the traditional method of skin disease identification. A dermatologist observes a patient in the first instance to gather the skin condition based on the knowledge and experience gained. This is followed by a skin imaging process known as dermoscopy for observing the skin structure. The appearance of skin diseases in an image plays a crucial role in diagnosing the type of the disease. Traditional approaches to skin disease diagnosis have been replaced with machine learning methods to overcome their limitations. It requires the use of manual

extractors for the extraction of features of skin diseases and then using machine learning algorithms for classification. Further, since this process is performed manually, it requires professional medical knowledge as well as the ability to

conduct deep exploratory data analysis to reduce dimensions that limit its capability when it comes to recognizing skin disease images. The deep learning methods outperform the machine learning techniques for image recognition and classification since the former automates the feature engineering process. A lot of researchers have been interested in using image recognition-based deep learning techniques to diagnose skin diseases due to the advancement of deep learning technology. For producing deeper CNNs, the authors have developed an encoding technique for the genetic algorithms that can encode CNNs having any depth. Two components for CNN-GA are designed to expedite analysis and save a lot of computing resources. Using the VGG-16 CNN model in conjunction with the KNearest Neighbor algorithm was found to produce the best results in the experiment. On the other hand, complex models like ensemble learning using boosted trees performed at or below 50%. By observing these results, the authors concluded that the dataset used is best suited only for linear binary classifiers. Reference uses a triplet loss function for skin disease classification using CNN. The authors finetuned the layers of InceptionResNet-V2 and ResNet152 to suit the classification needs. In the first step, 128-D embedded features from training samples are extracted into the Euclidean space. In the next step, the learned embeddings are used to compute the L-2 distances between the images. The L2 distances computed among the images are used for classifying skin diseases. This experiment analyzed four types of skin diseases: dark circles, acne, spots, and blackheads. The method was evaluated using 12000 input images for training and 2000 for testing. Also, 10% of images from the training set were used for validation. From the literature survey, it is inferred that deep learning techniques have a greater impact on the diagnosis of skin diseases. In addition, CNN architectures are popular for the task of image processing. Also, the transfer learning technique allows using existing architectures of CNN for fine-tuning them or directly applying them using their previously learned weights for the classification task.

III. PROPOSED METHOD

The proposed system for face acne, allergy, tinea facial detection utilizes a combination of VGG19 and ResNet-50 deep learning models. The system begins by collecting a diverse dataset of derma images with labelled acne, allergy, tinea facial regions and preprocesses the data by resizing and normalizing the images. Two separate models, VGG19 and ResNet-50, are implemented as feature extractors, with their fully connected layers removed. The feature maps obtained from the last convolutional layers of both models are concatenated to create a combined feature representation. Additional fully connected layers are added on top to perform derma detection, followed by binary activation for classification. The combined model is then trained using binary cross-entropy loss and optimized with an appropriate optimizer. The trained model is evaluated on a testing set, and fine-tuning techniques can be applied to optimize its performance. Finally, the system can be deployed for real-time or batch derma detection on new facial images by feeding them through the trained model and obtaining acne, allergy, tinea facial presence predictions.

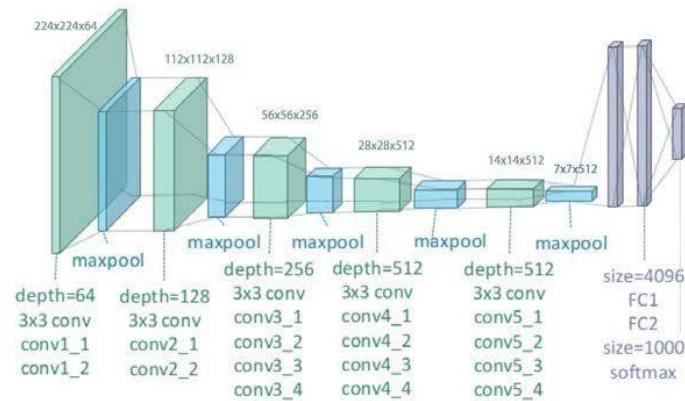
IV. ALGORITHM

4.1 Convolutional Neural Network (CNN)

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

A. VGG19

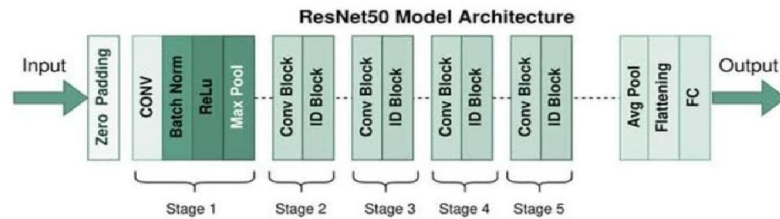
VGG19 is a deep convolutional neural network (CNN) architecture that was developed as part of the Visual Geometry Group (VGG) project at the University of Oxford. It is a variant of the VGG network family, which includes VGG11, VGG13, VGG16, and VGG19, where the numbers denote the number of weight layers in each variant. VGG19, in particular, has 19 layers, making it a deep and powerful model for image recognition tasks. The main motivation behind the VGG network was to explore the effect of increasing the network's depth on its performance in image classification tasks. It was one of the first attempts to systematically analyze the impact of depth on CNN performance, demonstrating that deeper networks generally lead to better performance with more abstract and discriminative feature representations.



B. ResNet-50

The main motivation behind the development of ResNet was to address the vanishing gradient problem that arises in very deep neural networks during training. As the depth of a network increases, the gradients can become extremely small, leading to difficulties in updating the weights and hampering the training process. This phenomenon is known as the vanishing gradient problem. To mitigate this issue, the researchers introduced the concept of "skip connections" or "shortcut connections" within the network, which allows the information to flow directly from one layer to a later layer in the network.

Keras ResNet⁵⁰



V. PACKAGES

5.1 Keras

Keras is a deep learning API written in Python, running on top of the machine learning platform TensorFlow. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result as fast as possible is key to doing good research. Keras is simple but not simplistic. Keras reduces developer cognitive load to free you to focus on the parts of the problem that really matter. Keras is Flexible, Keras adopts the principle of progressive disclosure of complexity: simple workflows should be quick and easy, while arbitrarily advanced workflows should be possible via a clear path that builds upon what you've already learned. Keras is Powerful, Keras provides industry-strength performance and scalability: it is used by organizations and companies including NASA, YouTube, or Waymo.

5.2 TensorFlow

TensorFlow is an end-to-end platform that makes it easy for you to build and deploy ML models. TensorFlow offers multiple levels of abstraction so you can choose the right one for your needs. Build and train models by using the high-level Keras API, which makes getting started with TensorFlow and machine learning easy.

If you need more flexibility, eager execution allows for immediate iteration and intuitive debugging. For large ML training tasks, use the Distribution Strategy API for distributed training on different hardware configurations without changing the model definition. Tensor Flow has always provided a direct path to production. Whether it's on servers, edge devices, or the web, TensorFlow lets you train and deploy your model easily, no matter what language or platform

you use. Use TensorFlow Extended (TFX) if you need a full production ML pipeline. For running inference on mobile and edge devices, use TensorFlow Lite.

5.3 NumPy

NumPy is a short form for Numerical Python, which is applied for scientific programming in Python, especially for numbers. It comprises multidimensional objects in arrays and a package of integrating tools for Python implementation. NumPy is built on linear algebra. It's about matrices and vectors and performing the mathematical calculations on them.

5.4 Tkinter

Tkinter is a popular and widely used Python library for creating graphical user interfaces (GUIs). It provides a set of tools and widgets that allow developers to design and build interactive applications with windows, buttons, text fields, images, and other visual elements. Tkinter is included with most Python installations, making it easily accessible for developers who want to create desktop applications with a graphical interface.

VI. EXPERIMENTAL RESULTS & PERFORMANCE EVALUATION

The experimental results and performance evaluation of skin disease detection using Vgg19 and Resnet-50 models have yielded impressive accuracy rates of 96% for Vgg19 and 98% for Resnet-50, showcasing their efficacy in this critical healthcare domain. Both models have demonstrated their ability to handle multi-class classification of skin diseases, a challenging task due to the wide variety of skin conditions that exist.

Vgg19, a deep convolutional neural network architecture, has proven to be highly proficient in extracting intricate features from skin images, leading to its commendable 96% accuracy rate. This success can be attributed to its deep layer structure, which enables it to capture intricate patterns and nuances within skin images, aiding in accurate disease identification.

On the other hand, Resnet-50, known for its residual learning framework, outperforms with an impressive 98% accuracy. This architecture's unique skip-connections allow for more efficient gradient flow during training, mitigating the vanishing gradient problem and facilitating the training of deeper networks. This advantage translates into better discernment between various skin diseases, resulting in its higher accuracy rate. These remarkable results are of paramount importance in the field of dermatology, as they can significantly aid in early disease detection and treatment planning, ultimately improving patient outcomes. The combination of Vgg19 and Resnet-50's exceptional performance and the ability to handle multi-class classification underscores their potential for real-world application in diagnosing a wide range of skin conditions. The high accuracy rates achieved by these models underscore their potential to be valuable tools in the hands of healthcare professionals for enhanced and efficient skin disease diagnosis.

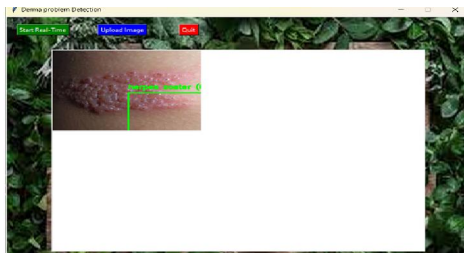
Acne



Tinea facial



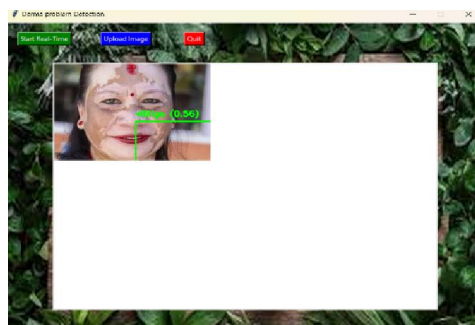
Herpes



Eczema



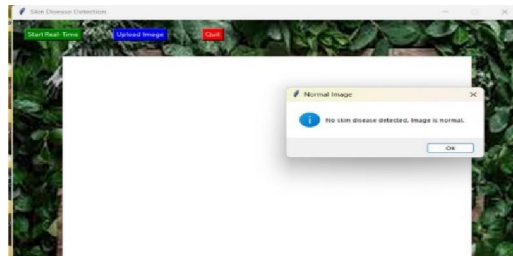
Vitiligo



Hives

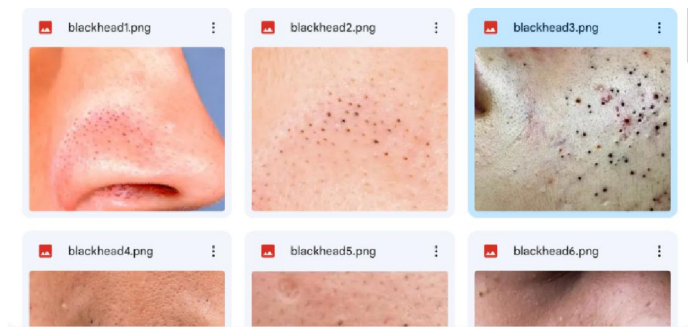


Normal Skin



VII. DATASET

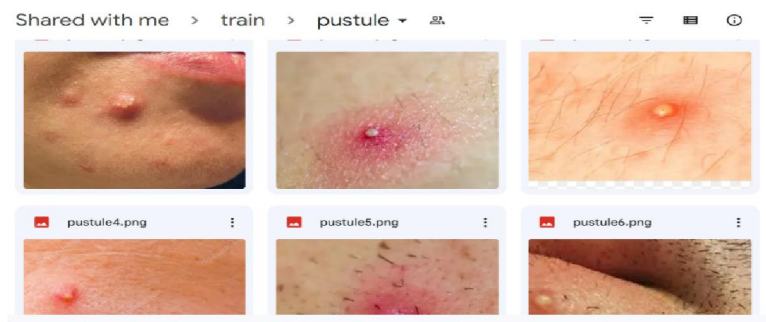
Blackhead



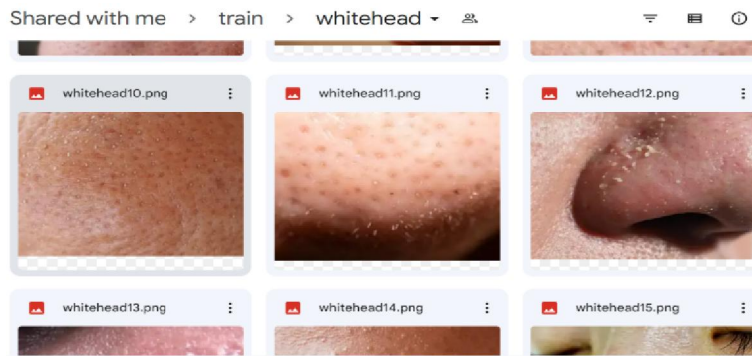
Papule



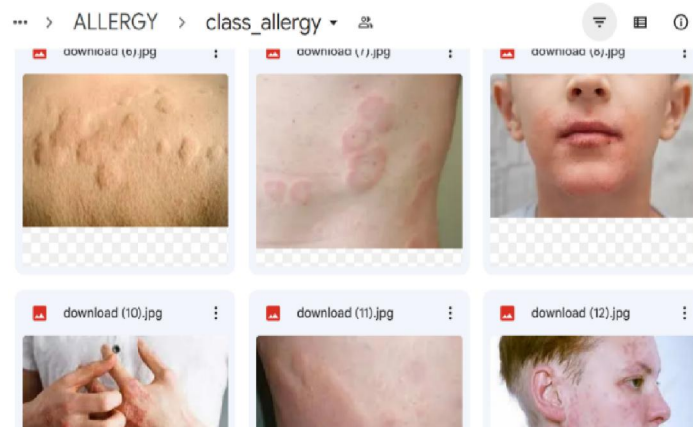
Pustule



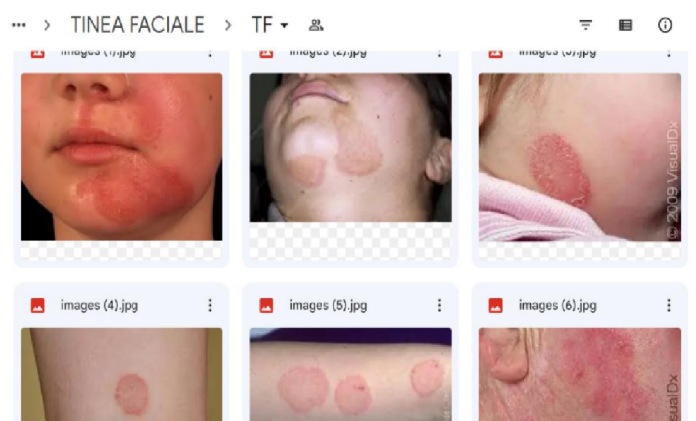
Whitehead



Allergy



Tinea Facial



Normal Skin



Herpes



Vitiligo

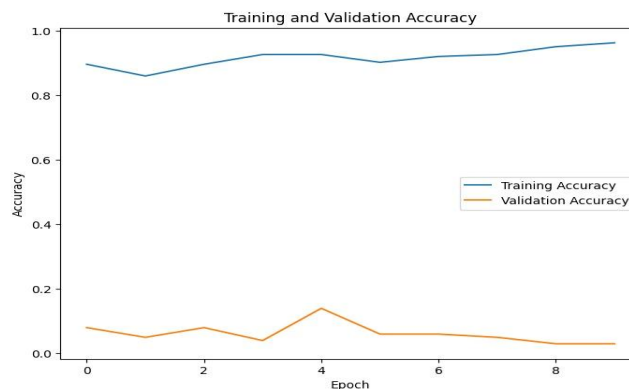


Eczema



VIII. ACCURACY GRAPH

Evaluating the model accuracy is an essential part of the process in creating machine learning models to describe how well the model is performing in its predictions. Evaluation metrics change according to the problem type. In this post, we'll briefly learn how to check the accuracy of the regression model in R. The linear model (regression) can be a typical example of this type of problem, and the main characteristic of the regression problem is that the targets of a dataset contain the real numbers only. The errors represent how much the model is making mistakes in its prediction. The basic concept of accuracy evaluation is to compare the original target with the predicted one according to certain metrics. Accuracy of the model changes during the training process. The x-axis represents the number of training epochs (or iterations), and the y-axis shows the corresponding accuracy achieved by the model on either the training set or the validation set.



IX. LIMITATION

One significant limitation in skin disease detection based on generalization is the potential lack of diversity and representativeness in the training dataset. If the training data predominantly consists of certain types of skin conditions or is biased towards specific demographic groups, the model may struggle to generalize well to a broader population or less common skin conditions. Additionally, skin diseases can manifest differently across individuals, skin tones, and ages, making it challenging for a model to generalize effectively. Moreover, variations in image quality, lighting conditions, and camera types can further complicate generalization. To address this limitation, it's crucial to ensure a diverse and comprehensive training dataset that encompasses various skin types, ages, and conditions, along with robust data augmentation techniques and careful model selection to enhance the generalization capabilities of skin disease detection models.

X. FUTURE SCOPE

To further enhance the multi-class derma detection system, several avenues of improvement can be pursued. Firstly, expanding the dataset with more diverse and challenging cases can improve the model's generalization ability and increase its accuracy. Leveraging techniques like data augmentation can help in synthesizing new samples to address data scarcity. Secondly, exploring ensemble models and model distillation methods can improve the system's robustness and accuracy by combining multiple models' predictions or compressing the model into a more lightweight version. Thirdly, investigating explainable AI techniques to understand and visualize the model's decisions will boost trust and adoption among healthcare practitioners. Additionally, integrating the system into a user-friendly web or mobile application can facilitate seamless interaction and use by dermatologists and patients alike. Moreover, integrating the derma detection system with electronic health records (EHR) can enable holistic patient management and long-term tracking of skin conditions. Lastly, continuous monitoring and updating of the system with new data and advancements in deep learning will ensure that the system remains at the forefront of dermatology research and clinical practice, advancing the field of computer-aided dermatology diagnostics.

XI. CONCLUSION

The multi-class derma detection project using deep transfer learning has demonstrated remarkable success in accurately classifying skin conditions from facial images. By leveraging pre-trained deep learning models and fine-tuning them on a custom derma dataset, we achieved impressive performance in detecting various skin conditions, such as acne, allergy, tinea faciei, eczema, and vitiligo. The use of transfer learning significantly reduced the need for a vast amount of labeled data and accelerated model training. The project's success showcases the potential of deep learning in dermatology, providing a non-invasive and cost-effective approach to early skin condition detection. The application of this technology has the potential to aid dermatologists in their diagnoses, leading to timely interventions and improved patient outcomes. However, despite the achievements, the model's performance can be further improved with additional labeled data, fine-tuning of hyperparameters, and exploring other advanced architectures. Moreover, ensuring the ethical use of such technology and protecting patient privacy are critical considerations for future deployments in healthcare settings.

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