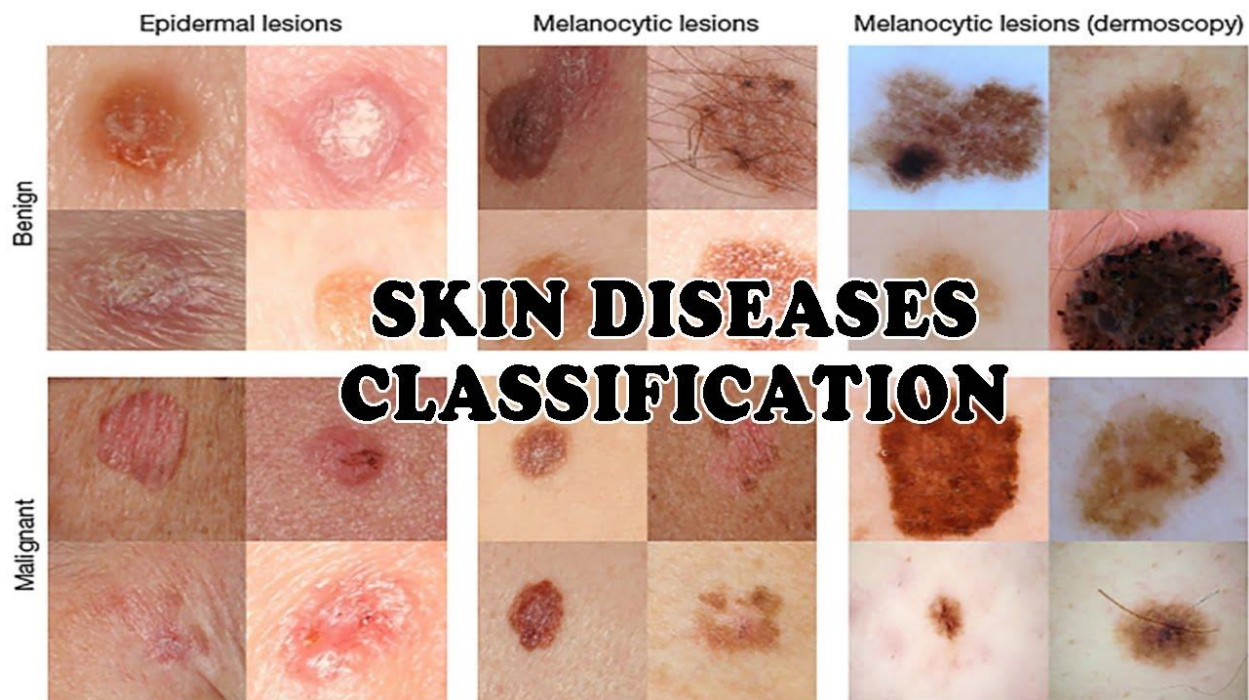


Skin Disease Classification

A skin disease classification project aims to develop a machine learning model or system that can accurately identify and categorize various skin conditions from images. By leveraging techniques such as image processing, convolutional neural networks (CNNs), and deep learning algorithms, the project processes skin images to classify conditions like Melanoma, Melanocytic nevus, Basal cell carcinoma, Actinic keratosis, Benign keratosis, Dermatofibroma, Vascular lesion, Squamous cell carcinoma dermatological disorders. The primary goal is to create a tool that can assist healthcare professionals in diagnosing skin diseases more efficiently and accurately, potentially aiding in early detection and treatment planning. The project typically involves collecting a large, diverse dataset of skin images, preprocessing the data, training a model, and evaluating its performance using metrics like accuracy and precision.



About the Dataset:

This dataset contains the training data for the ISIC 2019 challenge, note that it already includes data from previous years (2018 and 2017).

The dataset for ISIC 2019 contains 25,331 images available for the classification of dermoscopic images among nine different diagnostic categories:

Melanoma

Melanocytic nevus

Basal cell carcinoma

Actinic keratosis

Benign keratosis (solar lentigo / seborrheic keratosis / lichen planus-like keratosis)

Dermatofibroma

Vascular lesion

Squamous cell carcinoma

Model Selection

In the skin disease classification project, the model selection process involves choosing an appropriate architecture that can effectively handle the complexities of both image data and temporal sequences, given that you are using a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks.

1. Model Overview: The hybrid CNN-LSTM model combines the strengths of both architectures. CNNs are well-suited for extracting spatial features from images by applying convolutional filters, which are crucial for identifying patterns in skin lesions. LSTM networks, on the other hand, are effective at learning and capturing temporal or sequential patterns, making them useful

when handling data that may have temporal dependencies (such as video frames or time-series data).

2. CNN Component: The CNN is used for feature extraction from the input skin images. Multiple convolutional layers, followed by pooling layers, are applied to capture important features such as texture, color variations, and the shapes of skin lesions. These extracted features help in distinguishing between different types of skin diseases.

3. LSTM Component: The LSTM network comes into play when the model needs to understand sequences or dependencies within the features extracted by CNN layers. In the case of skin disease classification, the LSTM could be used to process sequences of image data (for example, in video or time-sequenced images of a lesion) to identify temporal patterns, helping the model predict disease progression or classifying images based on a sequence of frames rather than a single image.

4. Model Architecture: The architecture typically starts with several convolutional layers to extract hierarchical features from the input image, followed by an LSTM layer (or several layers) to capture the sequential dependencies among the extracted features. After the LSTM layer, the network often includes fully connected (dense) layers, followed by a softmax or sigmoid output layer, depending on whether the classification is multi-class or binary.

5. Model Evaluation and Fine-Tuning: Model selection involves evaluating the performance of the CNN-LSTM model using standard classification metrics such as accuracy, precision, recall, F1-score, and the confusion matrix. Cross-validation is used to assess generalization. Hyperparameter tuning, such as adjusting the number of convolutional filters, the number of LSTM units, learning rate, and batch size, helps to optimize the model's performance.

By combining CNNs and LSTMs, the model can effectively handle the spatial complexity of skin images and the sequential or temporal patterns that may arise in medical imaging, improving both classification accuracy and robustness.

[Code](#)