**GROUP I - PHASE 2 REPORT**

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**Aim of Project:**

This project aims to contribute to the field of dermatology by offering an efficient and accurate tool for skin disease classification, potentially improving diagnostic capabilities, and aiding in the timely treatment of various dermatological conditions.

**Existing Approaches:**

**Approach 1: Integrating Deep Learning for Skin Disease Detection**

Method:

This study presents a robust methodology for skin disease detection, utilizing deep learning techniques. A comprehensive dataset comprising clinical photographs of four prevalent skin diseases, validated by expert dermatologists, forms the basis of this research. Employing Convolutional Neural Networks (CNNs), particularly ResNet-50, known for its pre-trained capabilities on large datasets like ImageNet, the study extracts features crucial for classification. The dataset undergoes meticulous preprocessing using skimage, ensuring unbiased model evaluation by partitioning into training and testing sets.

Results:

The outcomes demonstrate an impressive accuracy of 87.42% in classifying skin diseases. Leveraging features extracted from images, the model effectively discerns between benign and malignant conditions. Evaluation metrics such as confusion matrices and the ROC curve, displaying an AUC of 0.87, underscore the model's discriminative prowess across disease categories.

Conclusion:

This study underscores the efficacy of amalgamating image processing with deep learning methodologies for precise skin disease detection. By harnessing pre-trained models and open-source tools, the research attains high accuracy levels, showcasing significant potential for real-world applications.

**Approach 2: Prototype Development for Skin Disease Detection Using Convolutional Neural Networks**

Method:

Focused on developing a prototype for skin disease detection, this study adopts Convolutional Neural Networks (CNNs) as the primary tool. The dataset, comprising images sourced from the Dermnet database and the internet, is augmented and preprocessed to optimize model performance. A custom CNN architecture comprising 13 layers is trained on the enhanced dataset.

Results:

The trained CNN model achieves a commendable accuracy rate of 73% on a dataset of 500 images, with precision, recall, and F1-score metrics calculated for each disease class. Despite not revealing the model's architecture, the study provides insights into its performance through confusion matrices and classification reports.

Conclusion:

This research underscores the potential of CNN-based approaches for skin disease detection, showcasing promising accuracy levels. Recommendations for further enhancements and validations using larger datasets are made to bolster the model's efficacy for practical deployment.

**Approach 3: Leveraging Region of Interest for Enhanced Skin Disease Classification**

Method:

This study focuses on early detection by isolating the surface texture of affected skin areas, known as Region of Interest (ROI). It employs a multi-step process involving skin image preprocessing, ROI determination, and feature extraction using the Gray Level Co-occurrence Matrix (GLCM) method. A Multi-Layer Neural Network (MLNN) structure is then utilized for classification, with features extracted from GLCM matrices serving as inputs.

Results:

The study reports compelling results, achieving an accuracy of approximately 92% across five disease classes. By effectively isolating ROIs and extracting texture features, significant improvements in classification accuracy and training time efficiency are observed, with dermatofibroma achieving 100% accuracy.

Conclusion:

This research underscores the efficacy of leveraging ROI-based features in conjunction with MLNN structures for enhanced skin disease classification. The findings highlight the potential of this approach in improving diagnostic accuracy and training efficiency, offering promising prospects for future research and practical applications.

**Proposed Solution:**

Our proposed solution entails the development of a robust machine learning-based system for the classification of skin diseases, leveraging advanced deep learning techniques. We prioritize meticulous preprocessing of the dataset, encompassing tasks such as data augmentation, normalization, and balancing to rectify any biases or inconsistencies. This pivotal preprocessing step is fundamental to augmenting the model's capacity for generalization and optimizing its performance.

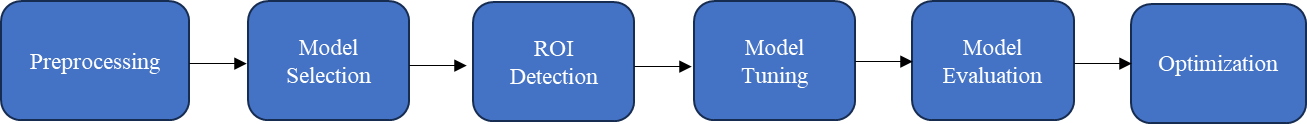
We plan to employ the MobileNetV2 architecture, a pre-trained convolutional neural network (CNN) recognized for its efficiency and efficacy in image classification tasks. By fine-tuning MobileNetV2 using the preprocessed dataset of skin disease images, our objective is to enhance its capability to accurately classify diverse dermatological conditions.

To further refine the model's performance and concentrate on crucial areas within skin images, we will integrate region of interest (ROI) detection methods. These methods entail the implementation of algorithms such as selective search or sliding window techniques to pinpoint and extract regions within the images that exhibit the most indicative features of specific skin diseases. By prioritizing these regions during the classification process, the model will allocate increased attention to areas harboring potentially significant diagnostic features, thereby elevating overall diagnostic accuracy.

In assessing the model, we will employ a range of performance metrics including accuracy, recall, precision, and F1-score. These metrics furnish comprehensive insights into the model's aptitude for correctly classifying skin diseases, encompassing its proficiency in identifying true positives, false positives, true negatives, and false negatives. Through meticulous analysis of these metrics, we can fine-tune the model parameters and optimize its performance to attain the desired levels of accuracy and reliability.

Harnessing state-of-the-art technology, our solution endeavors to expedite and enhance decision-making processes by facilitating the precise identification of skin diseases from images. Through this approach, we anticipate making a meaningful contribution to dermatology by furnishing an efficient and accurate tool for skin disease classification, ultimately enhancing diagnostic capabilities and facilitating timely treatment of various dermatological conditions.

**Design and Tools Used:**



**Fig. Basic Outline of Workflow**

* **Model Architecture and Workflow:**

Our approach involved the implementation of a Convolutional Neural Network (CNN) architecture, specifically MobileNetV2, for transfer learning in the context of skin disease classification. Transfer learning allowed us to leverage the pre-trained MobileNetV2 model, known for its efficiency in image recognition tasks, and fine-tune its layers to adapt it to the classification of various skin diseases from images. The model was trained using a diverse dataset encompassing various skin conditions, aiming to achieve accurate and generalized predictions.

* **Region of Interest (ROI) Detection:**

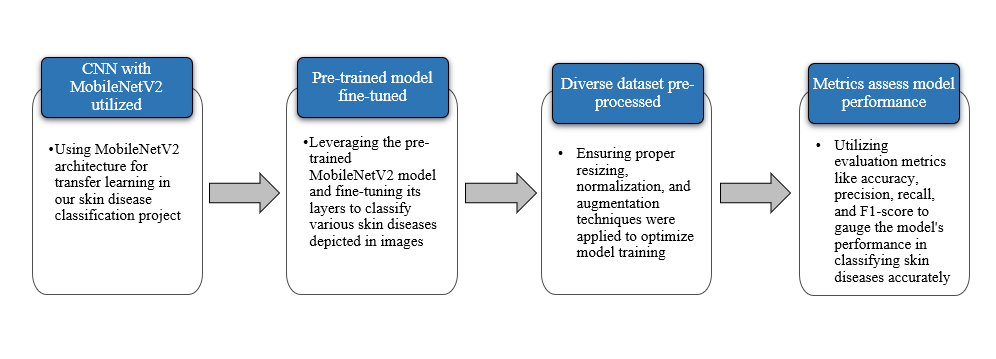
An integral enhancement to our project was the integration of Region of Interest (ROI) detection techniques. We utilized OpenCV and scikit-image libraries to implement ROI detection methods. This allowed the model to focus on specific areas within the images that are indicative of different skin conditions, improving the model's accuracy in disease identification by emphasizing critical regions.

* **Tools and Technologies Utilized:**
* Deep Learning Frameworks: TensorFlow and Keras were utilized for model development, leveraging their extensive capabilities in building and training neural networks.
* Image Processing Libraries: OpenCV, scikit-image, and PIL were instrumental in image manipulation, preprocessing, and ROI detection.
* Graphical User Interface (GUI) Development: We employed Tkinter, a Python library, to create a user-friendly GUI interface for easy access to the model. This GUI allowed users to interact with the model, input images, and visualize predictions effortlessly.
* Data Handling and Analysis: NumPy and Pandas were used for data manipulation and analysis, ensuring efficient data handling and preprocessing.
* **Data Preprocessing:**

A crucial step involved the curation and preprocessing of a comprehensive dataset consisting of diverse skin problem images. The dataset underwent resizing, normalization, and augmentation techniques to ensure uniformity and to enhance the model's robustness in handling various image types.

* **Evaluation Metrics:**

For assessing the model's performance, we employed evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics provided insights into the model's effectiveness in classifying different skin diseases accurately.



**Fig. Design**

**Codes:**

**Skin\_Disease\_Detection.py:**

import os

from tensorflow.keras.preprocessing.image import ImageDataGenerator

from tensorflow.keras.applications import MobileNetV2

from tensorflow.keras import layers

from tensorflow.keras import models

from tensorflow.keras import optimizers

project\_directory = r'C:\Users\Lenovo\Downloads\skin-disease-datasaet'

train\_data\_dir = os.path.join(project\_directory, 'train\_set')

test\_data\_dir = os.path.join(project\_directory, 'test\_set')

img\_width, img\_height = 224, 224

batch\_size = 32

train\_datagen = ImageDataGenerator(rescale=1./255,

                                   shear\_range=0.2,

                                   zoom\_range=0.2,

                                   horizontal\_flip=True)

test\_datagen = ImageDataGenerator(rescale=1./255)

train\_generator = train\_datagen.flow\_from\_directory(train\_data\_dir,

                                                    target\_size=(img\_width, img\_height),

                                                    batch\_size=batch\_size,

                                                    class\_mode='categorical')

test\_generator = test\_datagen.flow\_from\_directory(test\_data\_dir,

                                                  target\_size=(img\_width, img\_height),

                                                  batch\_size=batch\_size,

                                                  class\_mode='categorical')

base\_model = MobileNetV2(weights='imagenet', include\_top=False, input\_shape=(img\_width, img\_height, 3))

model = models.Sequential()

model.add(base\_model)

model.add(layers.GlobalAveragePooling2D())

model.add(layers.Dense(128, activation='relu'))

model.add(layers.Dropout(0.5))

model.add(layers.Dense(len(train\_generator.class\_indices), activation='softmax'))

model.compile(optimizer=optimizers.Adam(learning\_rate=0.0001),

              loss='categorical\_crossentropy',

              metrics=['accuracy'])

history = model.fit(train\_generator,

                    steps\_per\_epoch=train\_generator.samples // batch\_size,

                    epochs=15,

                    validation\_data=test\_generator,

                    validation\_steps=test\_generator.samples // batch\_size)

model.save('skin\_disease\_model.h5')

**Test.py:**

from tensorflow.keras.models import load\_model

from tkinter import filedialog

from tensorflow.keras.preprocessing import image

import numpy as np

model = load\_model('skin\_disease\_model.h5')

img\_width, img\_height = 224, 224

batch\_size = 1

test\_datagen = image.ImageDataGenerator(rescale=1./255)

test\_generator = test\_datagen.flow\_from\_directory('test\_set',

                                                  target\_size=(img\_width, img\_height),

                                                  batch\_size=batch\_size,

                                                  class\_mode='categorical',

                                                  shuffle=False)

while True:

    img\_path = filedialog.askopenfilename(filetypes=[("Image Files", "\*.png;\*.jpg;\*.jpeg")])

    img = image.load\_img(img\_path, target\_size=(img\_width, img\_height))

    img\_array = image.img\_to\_array(img)

    img\_array = np.expand\_dims(img\_array, axis=0)

    img\_array /= 255.0

    predictions = model.predict(img\_array)

    predicted\_class = np.argmax(predictions)

    class\_labels = list(test\_generator.class\_indices.keys())

    predicted\_label = class\_labels[predicted\_class]

    print("Predicted Class:", predicted\_label)

**References:**

**[1]** Syed Inthiyaz, Baraa Riyadh Altahan, Sk Hasane Ahammad, V Rajesh, Ruth Ramya Kalangi, Lassaad K. Smirani, Md. Amzad Hossain, Ahmed Nabih Zaki Rashed, Skin disease detection using deep learning, Advances in Engineering Software, Volume 175, 2023.

[2] T. A. Rimi, N. Sultana and M. F. Ahmed Foysal, "Derm-NN: Skin Diseases Detection Using Convolutional Neural Network," *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2020, pp. 1205-1209.

[3] T. H. Nguyen and B. V. Ngo, “ROI-based features for classification of skin diseases using a multi-layer neural network,” Indonesian Journal of Electrical Engineering and Computer Science, vol. 23, no. 1, pp. 216–228, Jul. 2021.