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Transparent Neural Network for Skin Lesion Classification: A Deep Learning Perspective

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Abstract

Skin cancer is quickly become more prevalent worldwide, constrained by the limited resources allocated for its management. This study endeavors to refine the precision of identifying skin lesions by employing sequential module architecture in CNNs. In this research, proposes a model aimed at improving the accuracy of skin cancer detection by utilizing convolutional neural networks in conjunction with image processing methods, a facet of machine learning, deep learning. The dataset comprises over 3000 images portraying individuals with skin disorders, categorized into two groups: malignant and benign. We presented CNN alongside seven diverse architectures to evaluate the accuracy of skin cancer images. By conducting a comparative analysis, we identified the optimal architecture tailored to this specific problem. In our model, MobilenetV2 exhibited the lowest performance, attaining an accuracy rate of around 54.545 percent. The sequential module architecture proved to be the most suitable for our dataset, trained using images sourced from kaggle.com. This architecture yielded an accuracy rate of nearly 92.07 percent for our dataset. Issues like limited computational power, image quality within the dataset, and complexities in image pre-processing can result in decreased accuracy.

Keywords **–** Convolutional Neural Networks (CNNs), Sequential Module Architecture, Identification of Skin Cancer, Sophisticated Deep Learning Approaches, Categorization of Skin Lesions.

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I. Introduction

In recent times, the risk to life associated with skin diseases has heightened, as certain conditions may unexpectedly manifest on the skin. Skin ailments are widely recognized as some of the most common diseases globally, impacting over 900 million individuals globally. Moreover, an estimated 18% of the global population experiences malignant growths on their skin annually. As a result, skin diseases rank as the fourth most prevalent cause of human illness. When healthy cells undergo abnormal changes and proliferate uncontrollably, a tumor is formed. This phenomenon can give rise to both cancerous and noncancerous tumors. Malignant tumors are those that have the potential to grow and

spread to other regions of the body [1]. A benign tumor may emerge, but it tends to stay localized without spreading. Skin cancer results from abnormal growth of skin cells and is the most prevalent cancer globally, occurring universally. Annually, it is estimated that more than 3.5 million cases of different types of melanomas are identified [2], [3].

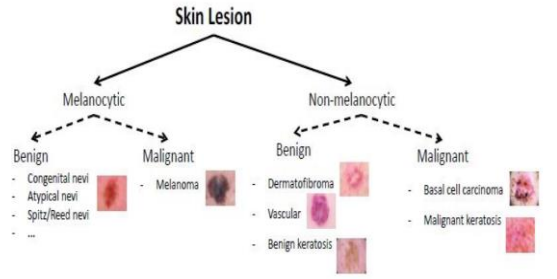

Fig. 1. Skin lesions Organization: melanocytic and non-melanocytic are the two main categories; each could be benign or malignant. The last level is the diagnosis of lesions [1].

The skin, one of the body's largest organs, undergoes continuous growth and changes throughout life. A skin lesion refers to any abnormality or deviation in the appearance or growth of the skin compared to its surrounding tissue. Lesions can vary in their type, shape (both individual and clustered), texture, color, affected area, and distribution (whether random or patterned, symmetric or asymmetric). Skin lesions can be categorized into 2032 types, organized hierarchically [4] as depicted in figure 1 this hierarchy starts with two main groups: melanocytic and non-melanocytic. Melanocytic lesions are characterized by the presence of melanocytes and melanin pigment, while non-melanocytic lesions lack these features. Melanocytic lesions possess eight overarching characteristics that facilitate a comprehensive classification of pigmented skin lesions. Additionally, they exhibit fourteen specific features that provide more precise details about each lesion [5]. Non-melanocytic lesions may have a yellow or orange appearance due to keratin, and they can also appear red, purple, blue, or black because of the presence of hemoglobin [6]. Lesion falling into either category may be categorized as either benign (non-cancerous) or malignant (cancerous). The endpoints illustrated in figure1 represent diagnoses of lesions, including melanoma basal cell carcinoma, vascular lesions, nevi, and others.

In common CAD (Computer- Aided Diagnosis) systems, deep learning (DL) algorithms like convolutional neural networks (CNNs) with sequential module Architure, along with image processing methods, play a vital role [7]. There remains skepticism among dermatogists and patients regarding the use of CAD systems. Largely because the processing cycle involved in model learning and feature encoding is not thoroughly understood. The lack of a logical explanation for DL models creates an obstacle for dermatologists in making accurate decisions. At times, experts find it challenging to grasp the predictions made by the model. Imagine a situation where a DL model achieves an 87% accuracy rate in diagnosing skin cancer. Understanding why the model produces inaccurate results in the remaining 13% of cases and how to improve these decisions can be quite challenging. As a result, there is a need to create reliable techniques for gaining insight into the opaque decisions. These techniques are often denoted as interpretable deep learning or XAI (Explainable Artificial I intelligence) [8]. In this research, the state-of-the-art pre-trained deep learning algorithm, sequential module, is utilized on kaggle.com to classify skin lesions into two and seven categories, respectively. We extensively train the model to address the imbalance in the dataset and demonstrate its impact on the accuracy of the model. In our proposed

methodology, we utilize the classification of seven types of skin lesions to achieve higher accuracy.

As per the world health organization (WHO), skin cancer stands out as one of the most frequent types of malignancies in the medical sector. Deep learning techniques are continuously utilized to improve the precision of detecting diverse medical issues more effectively. Numerous innovative techniques have emerged to expedite the process while achieving the highest level of accuracy. This study presents a model aimed at enhancing the detection of skin cancer through the integration of image processing methods and convolutional neural networks, which are components of deep learning within the machine learning domain. The dataset includes nearly 3000 images of individuals with skin conditions, categorized into two groups: malignant and benign. We presented CNN alongside seven diverse architectures to evaluate the accuracy of skin cancer images. Our aim was to identify the optimal architecture for addressing this particular issue through comparative analysis. We tested ResNet50, VGG16, Inception V3, VGG 19, Xception, M obileNetV2, and MobileNet architectures to pinpoint the most appropriate model for our dataset. Our objective was to identify the model that best fits the specific characteristics of our dataset. Improvements to our model could be achieved by adjusting parameters such as increasing the number of epochs, reducing batch size, altering dropout values, and so forth. In simpler terms, this would obviously require more time. In our evolution, MobileNet V2 demonstrated the lowest accuracy at approximately 54.545% on the contrary; we determined that the sequential module architecture was the most effective for our dataset. In simpler terms, factors like limited computational power and issues with dataset images quality or pre-processing can lead to decreased accuracy despite using this architecture, which achieved nearly 92.07% accuracy for our dataset.

The dataset, sourced from kaggle.com, encompasses images classified into 7 categories: MEL (Melanoma), NV (Melanocytic nevus), BCC (Basal cell carcinoma), BKL (Benign keratoses, including solar lentigo, seborrheic keratoses, lichen planus- like keratoses), SCC (Squamous cell carcinoma), normal (Normal human skin), and UNK (Undefined *) – a compilation of classes such as actinic keratoses, dermatofibroma, vascular lesion, chickenpox, warts, and molluscum, sourced from other datasets.

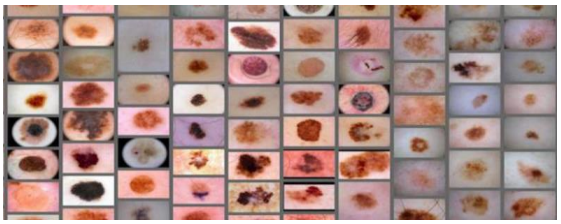

Figure 2: Seven Classification of Dataset

II. Literature Review

Skin condition classification using deep learning has become a dynamic field of study in recent years, showing promising outcomes for accurate and efficient diagnosis of diseases. The technique for classifying skin lesions via fine-tuned neural network is delineated in [9].To counter dataset imbalance, skin lesion image are Resembled. Subsequently, a Hybrid model consisting of Dense Net and U-Net is trained for Segmentation purposes, and Subsequently Utilized to fine-tune the classifiers mentioned. The encoder portion of the segmentation model's architecture is then trained to categorize the seven different Skin disorders. Taken CNN-based features into account, a model was created using

only 900 photos, which seems insufficient for effectively training deep learning techniques. Through the DRN-50 approach, thus achieved an accuracy of 85.5%; using the VGG-16 method, 82.6%; and With the GoogleNet technique 84.7% [10].

A study investigates the efficacy of a deep learning algorithm for classifying skin lesion. The authors utilize a dataset comprising more than 12,000 dermatoscopic image to train a CNN. They then use a different validation set to evaluate the CNN's performance. They assert that diagnostic accuracy for melanoma is 91%, which aligns with the proficiency of experienced dermatologists [11].

The main objective of the proposed system is to classify skin lesion using deep learning, particularly by utilizing a CNN with a sequential model approach [12]. The paper's methodology entails examining a dataset sourced from kaggle.com, which comprises 10,015 instances representing seven distinct types of skin lesion. The procedures outlined in this paper involved training the model using CNN, Leading to an accuracy rate of 92%. In essence, the decoder network's objective is to upscale the encoder's feature maps to produce full-resolution feature maps mirroring the original input. In essence, the primary focus of the method is to classify skin lesions using deep learning, specifically employing a CNN approach [13]. The method described in this paper involves the evaluation of a dataset obtained from kaggle.com, containing 10,015 instances representing seven various types of skin lesions. The method detailed in the paper involved training the model using CNN, resulting in accuracy of 92%.

In essence, the research showcases that employing transfer learning leads to an autonomous system with enhanced classification accuracy in identifying skin lesions. The Alex Net has been refined through transfer learning by adjusting the weights of the architecture and expanding the dataset with fixed and random rotation angles. The proposed approach has achieved accuracies of 96.86%, 97.70%, and 95.91%, respectively [14].

A recently developed practical method for organizing MCS cancer utilizes a seven –category approach. Transfer learning is applied using a pre-trained sequential module structure to train the seven classes from a dataset. Alternatively, the accuracy, precision, recall, and F1 Score for the categories are 83.1%, 89%, 83%, and 83%, respectively [15].

These results suggest that deep learning is capable of accurately and effectively classifying skin diseases. More research is needed to address the drawbacks and limitations of existing strategies, including the need for more diverse datasets and models that are easier to interpret.

III. Input Dataset

In essence, this study emphasizes the importance of utilizing Dermoscopic – acquired images of skin cancer due to their widespread usage. The system utilized the kaggle.com HAM 10000 dataset, which contains a significant collection of images depicting typical melanin skin lesions from various sources. The dataset includes 10015 Dermoscopic images representing seven specific types of skin cancer. The dataset contains 6705 images depicting melanocytic nevi (nv), 1113 images representing melanoma (mel), 1099 images for benign keratoses – like lesions (bkl), 514 images

for basal cell carcinoma (bcc), 327 images for actinic kertoses (akiec), 142 images illustrating vascular lesions (va), and 115 images for dermatofibroma (df).

For straightforward and efficient management the photographs in the kaggle.com HAM10000 dataset will be organized into folder according to their corresponding disease classes. The 'base directory' is set up, where the "train directory" and "validation directory" are then created as subdirectories within it. Within both the "train directory" and "validation directory" seven folders where created, named "nv", "mel", "bkl", "bcc", "akiec", "vas", and "df". Each folder represents one of the seven different types of skin cancer lesion present in the dataset. Figure 1 shows the data samples for each type of skin disease category.

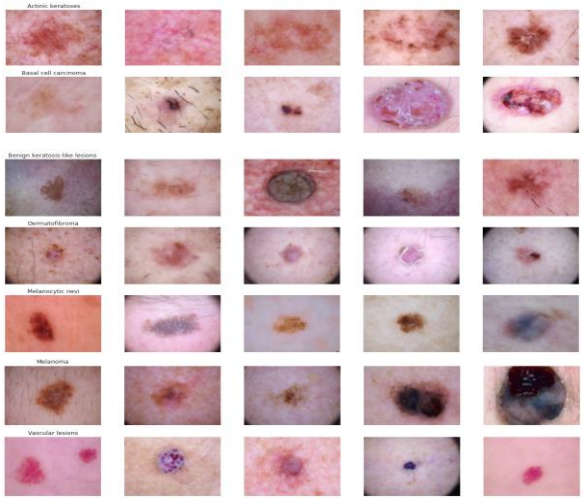

Figure3. Actinic keratoses, Basal cell carcinoma, Benign keratosis-like lesions, Dermatofibroma, melanocytic nevi, Melanoma, Vascular lesions.

IV. Proposed Methodology

Dermoscopy is a non-invasive diagnostic technique used by doctor to examine skin lesions and identify skin cancer. Deep learning algorithms have been increasingly used to diagnose skin cancer by analyzing Dermoscopic images. Transfer learning is commonly applied in classifying Dermoscopic images, often utilizing pre-trained CNN models like sequential. This involves using a pre-trained sequential architecture, as depicted in

Figure 4, for the general classification of Dermoscopic images.

A. Data Preparation

Acquire a significant dataset of dermoscopy images, each properly labeled with corresponding categories (e.g. melanoma, nerves, etc...). Standardize the size and format of the photographs through preprocessing, ensuring uniformity across the dataset.

B. Preprocessing

To enhance the training dataset and reduce the risk of over fitting, utilize data augmentation techniques such as rotation, flipping, and scaling.

C. Model Selection

Remove the final layers of a pre-trained CNN model like sequential, and incorporate additional layers to more accurately suit the categorization task, substituting the removed layers with new ones.

D. Transfer Learning

Keep the pretrained layers of the model fixed while training only the newly added layers using the dermoscopy images. This method enables the network to leverage the features learned by the pre-trained model while also acquiring characteristics unique to dermoscopy images.

E. Fine-tuning

Once the new layers are trained, select a few previously trained layers to unfreeze and retrain them with a lower learning rate to fine-tune the entire network, leading to improved accuracy.

F. Model Evaluation

Evaluate the model's performance with validation data, and adjust the model's design and configurations as needed to improve its effectiveness.

G. Prediction

Use the trained model to make predictions for the labels of new dermoscopy images.

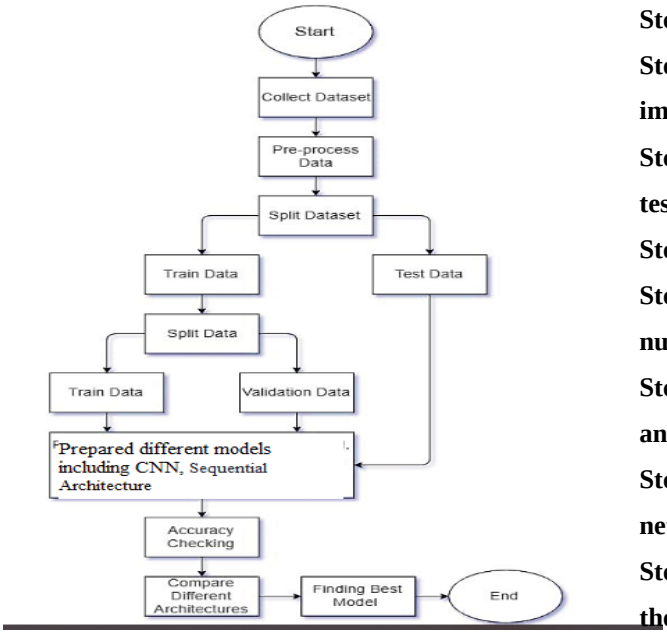

Figure 4: Proposed system depicted by flowchart.

Because this is a general approach, specific details may differ depending on the dataset and the classification task being performed. For classifying dermoscopy images using transfer learning with the MobileNet architecture, this approach offers a sensible starting point.

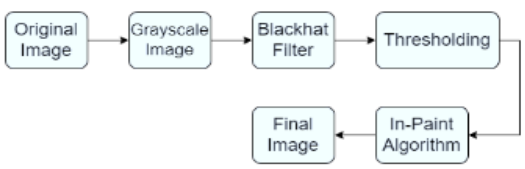

Figure 5: Pre-processing

In this kernel, I've outlined a step-by step process for building and evaluating a model to classify 7 classes of cancer. Specifically, I've followed these 14 steps:

Step 1: Bringing in necessary libraries.

Step 2: Creating a mapping between images and their corresponding labels.

Step 3: Loading and handling data.

Step 4: Refining or preparing the data.

Step 5: Analyzing or exploring the data (AED).

Step 6: Importing and adjusting the size of images.

Step 7: Splitting the dataset into training and testing sets.

Step 8: Standardizing or scaling the data.

Step 9: Transforming categorical labels into numerical values.

Step 10: Partition the training data into training and validation subsets.

Step 11: Developing a Convolutional neural network (CNN).

Step 12: Setting up the Optimizer and fine-tuning the learning rate.

Step 13: Training the model with the data.

Step 14: Assessing the model's performance (testing and validation accuracy, generating a confusion matrix, and analyzing misclassified instances).

V. Results and Discussion

Our model includes preparing the dataset, training deeply and evaluating performance. These steps are conducted in both experiments.

a) The first experiment: Aims to extensively train all layers of pretrained models using the original data without addressing its imbalance problem. During the preprocessing phase, the dataset images

are partitioned into 8470 training, 993 validation, and 552 testing images.

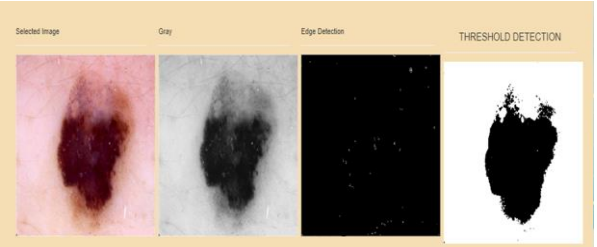

Figure 6. Output of skin lesion thresholding.

The dataset for multi-class classification includes 1600 skin lesion images; each sized 224X224 pixels. These images are evenly divided into eight classes, with 200 images per class. There is an additional dataset for binary classification with 400 images, evenly split between 200 malignant and 200 benign images. The process included using a pre-trained model for automatic feature learning and preprocessing, followed by splitting the dataset into training and testing sets with an 80-20 ratio.

b) Precise identification of skin lesion: our deep learning model accurately recognizes and sorts various types of skin lesions, contributing to the early detection of potential skin cancers.

c) Quicker assessment: utilizing deep learning algorithms, our system expedites the process of diagnosing skin cancer, leading to prompt medical intervention and treatment.

d) Enhanced patient results: the early detection enabled by our deep learning- based skin cancer detection system results in better patient outcomes, such as increased survival rates and decreased morbidity.

e) Improved accessibility: our solution can be implemented in diverse healthcare environments, including remote and underserved areas, enhancing access to timely and dependable skin cancer detection services.

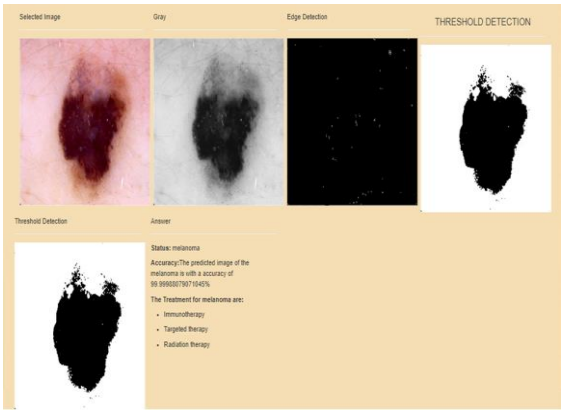

Figure 7: Prediction on sample images from the dataset along with their labels and accuracy.

VI. Conclusion and Future Work

As the number of patients with skin diseases rises daily, the issue of classification becomes more difficult. The need for automated classifiers is set to increase, particularly given the promising results achieved thus far. We suggest a system to aid dermatologists and patients in diagnosing skin conditions. We created a created classifier capable of identifying seven prevalent skin diseases from images. This involved developing a model using deep convolutional neural networks, which can determine the type of skin disease shown in an input image. Furthermore, we developed an application to serve as an interface for our system. This application captures live images from the patient and categorizes it accordingly. The attained accuracy of 92.07% is promising. Nonetheless, there are opportunities for enhancing accuracy and avenues for future research, as summarized below : i) utilize larger datasets, ii) focus on binary classification for each of the seven diseases individually, iii) conduct more rigorous tuning of hyper parameters, although this process can be time-consuming, iv) implement cross – dataset validation,

which is skin to cross-validation but involves using distinct datasets, v) explore feature engineering and selection techniques, and iv) incorporating clinical data such as age, race, skin type, or gender as inputs to the classifier.

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