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MELANOMA DETECTION USING DEEP LEARNING

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Abstract:

This project is a innovative and revolutionary deep learning based web application that aims to detect melanoma from user input.The primary aim of this project is to develop a system that can accurately detect and distinguish melanoma lesions from Non melanoma lesions.The proposed system uses a trained neural network model to distinguish between melanoma lesions and non melanoma lesions.The early detection of melanoma is crucial as it increases the survival rate of the patients.Melanoma is often diagnosed at the later stages thus increasing the fatality rate.The proposed system aims to overcome these limitations by aiming to detect melanoma from an input image provided by the user.Furthermore the system aims to assist medical professionals in the detection of melanoma.The projects outcomes demonstrate the advantages of the system and successful implementation

I.INTRODUCTION

At least 40 percent of all malignancies are skin cancers, making them one of the most frequent forms of the disease. A total of over 300,000 new instances of melanoma were diagnosed in 2018, making it the 19th most frequent disease in human civilization.

Studies demonstrate that the application of modern computer technologies, such as image processing mechanisms, in processes connected to early identification of this disease might aid doctors in healing this cancer, even though cancer diagnosis is reliant on interventional treatments like surgery, radiation, and chemotherapy. Cancer of the skin, which covers the biggest area of the human body, is the most frequent form of the disease in the United States. Skin protects the body from excessive heat, sunshine, and injury or illness. The epidermis, dermis, and hypodermis are the skin's three layers. The epidermis is the outermost layer of skin and is responsible for producing the skin's color and forming a watertight barrier. The dermis is the skin's middle layer and is home to sweat glands, hair follicles, and rough connective tissue. Finally, the connective tissue and fat that make up the hypodermis form the base of the skin. Skin cancer is the greatest risk to the skin's health.

II. LITERATURE SURVEY

1.**TITLE**

M. Çakmak and M. E. Tenekecı, "Melanoma detection from dermoscopy images using Nasnet Mobile with Transfer Learning," M. Çakmak and M. E. Tenekecı, "Melanoma detection from dermoscopy images using Nasnet Mobile with Transfer Learning,"

DESCRIPTION

Nasnet Mobile architecture is classified by retraining using the HAM10000 skin lesion dataset provided by ISIC 2018.The accuracy rate obtained with the **Nasnet Mobile model** was increased to **89.20%** before data increase and **97.90%** after data increase.

2.TITLE

B. Ganguly, et al."A Deep learning Framework for Eye Melanoma Detection employing Convolutional Neural Network,"

DESCRIPTION

Transfer learning using a pre-trained framework is shown to aid in improving the detection accuracy of a **generic Convolutional Neural Network (CNN)**. Additionally, data augmentation is used to boost the efficiency of the model.

Although the proposed method requires a huge computation, a high accuracy rate of **91.76%** is achieved, outperforming the eye melanoma detection using an artificial neural network (ANN).

3.TITLE

A. R. F. dos Santos et al., "Melanoma Classification Approach with Deep Learning-Based Feature Extraction Models,"

DESCRIPTION

This work developed a disease detection system using **AlexNet and VGG-F convolutional architectures**, trained with images of skin lesions The VGG-F architecture obtained the best result, with an accuracy of **91.54%** and a precision of **91.64%** given by the K-Nearest Neighbor.

4.**TITLE**

T. Guergueb and M. A. Akhloufi, "Melanoma Skin Cancer Detection Using Recent Deep Learning Models,"

DESCRIPTION

This study presents the use of recent deep CNN approaches to detect melanoma skin cancer and investigate suspicious lesions. The obtained results show that the best performing deep learning approach achieves high scores with an accuracy and Area Under Curve (AUC) above **99%.**

5.**TITLE**

V. Vipin, et al."Detection of Melanoma using Deep Learning Techniques: A Review," doi: 10.1109/ICCISc52257.2021.9484861.

DESCRIPTION

Numerous deep learning approaches may be used for Melanoma detection, however their results vary greatly because of the inherent variability in factors like learning rates, optimizers, batch size, etc. In this paper machine learning and deep learning algorithms applied for better classification, segmentation, and analysis of melanoma.accuracy of **91.63%** is achieve.

III. IMPLEMENTATION

1. DATASET DESCRIPTION

The Dataset is a merged dataset from publicly available datasets "isic challenge 2017","DERMNET skin disease library" and "isic challenge 2018" ,The dataset consists of 9 classes and 2 directories for test and train.The dataset contains images of melanoma lesions and various skin lesions including(Actinic Keratosis Basal Cell Carcinoma and other Malignant Lesion,Atopic Dermatitis Photos,Eczema Photos, and Moles,Nail Fungus and other Nail Disease,Psoriasis Lichen Planus and related diseases,Seborrheic Keratoses and other Benign Tumors,Tinea Ringworm Candidiasis and other Fungal Infections,Warts Molluscum).The dataset contains 26,642 training images and 2395 test images

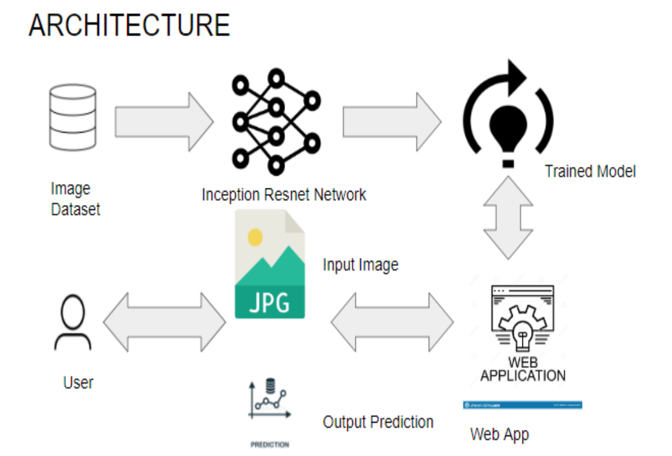
Training data:

Actinic Keratosis Basal Cell Carcinoma	4472 images
Atopic Dermatitis	1746 images
Eczema Photos	2912 images
Melanoma Skin Cancer	3603 images
Nail Fungus	1040 images
Psoriasis Lichen Planus	3460 images
Seborrheic Keratoses	3218 images
Tinea Ringworm Candidiasis	3002 images
Warts Molluscum	3189 images

Testing data:

Actinic Keratosis Basal Cell Carcinoma	288 images
Atopic Dermatitis	123 images
Eczema Photos	309 images
Melanoma Skin Cancer	116 images
Nail Fungus	261 images
Psoriasis Lichen Planus	352 images
Seborrheic Keratoses	343 images
Tinea Ringworm Candidiasis	352 images
Warts Molluscum	272 images

2. SYSTEM FRAMEWORK:



The dataset is used in training the inception_resnet v2 architecture and the trained model is saved,the user interacts with the web application by inputting a image as input and the web application passes the input to the trained model to make predictions and the application outputs the prediction to the user

IV. MODULES

1.DATASET PREPROCESSING

The dataset is downloaded into a local device and the images are resized to
Reduce time complexity
Before resizing:

dimensions:720*422

Resizes image:

Dimensions:200*200

2. TRAINING OF MODEL

The model is trained by using the inception_resnet architecture on the dataset for 25 epochs ,the model outputs the following parameters,Here adam optimiser which is a extended version of stochastic gradient descent is used,the model outputs a total of 54,350,569 parameters out of which 54,290,025 are trainable parameters and 60,544 are non trainable parameters

Model: "sequential_2"

Layer (type)	Output Shape	Param #
inception_resnet_v2 (Functional)	(None, 5, 6, 1536)	54336736
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 1536)	0
dense (Dense)	(None, 9)	13833

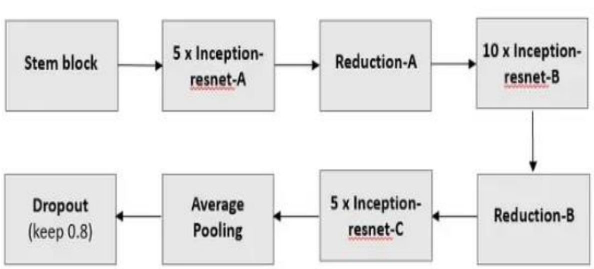
Total params: 54,350,569
Trainable params: 54,290,025
Non-trainable params: 60,544

3.MEASUREMENT OF ACCURACY

A validation accuracy of **95.11%** is obtained in the final epoch

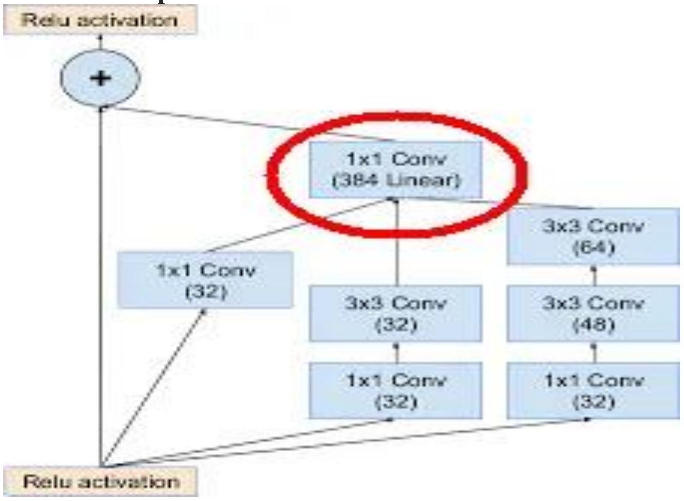
V. ARCHITECTURE DIAGRAM

INCEPTION_RESNET_V2



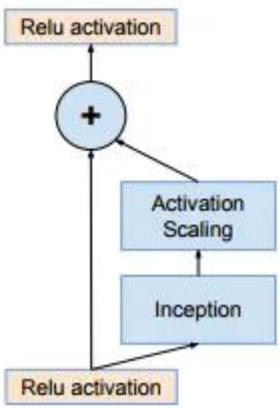
Using the Inception-ResNet architecture, exceptional performance can be achieved at relatively low computational costs by combining the Inception architecture with residual connections.

Residual Inception blocks



Prior to the addition, each Inception block is followed by a filter expansion layer (1 x 1 convolution without activation) which allows scaling up the dimensionality of the filter bank before the addition.Inception-ResNet uses batch-normalization only on top of traditional layers, not on top of summations

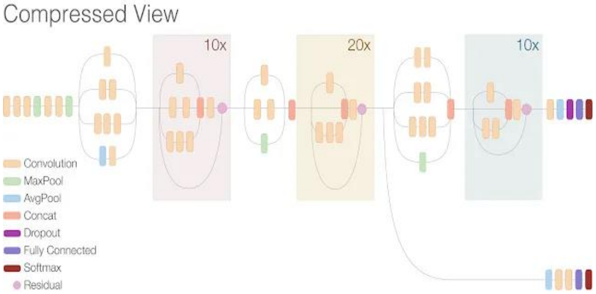
Scaling of Residuals



The residual variants display instabilities if the number of filters exceeds 1000, which means the network will die very early in the training process. After a few tens of thousands of iterations, the last layer before the average pooling will produce nothing but zeros.

Inception Resnet V2 Network

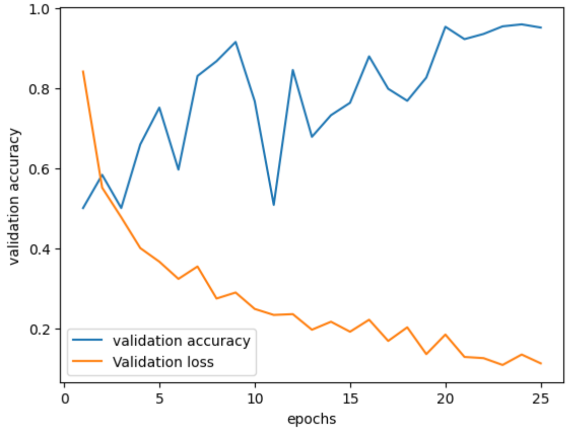
Compressed View



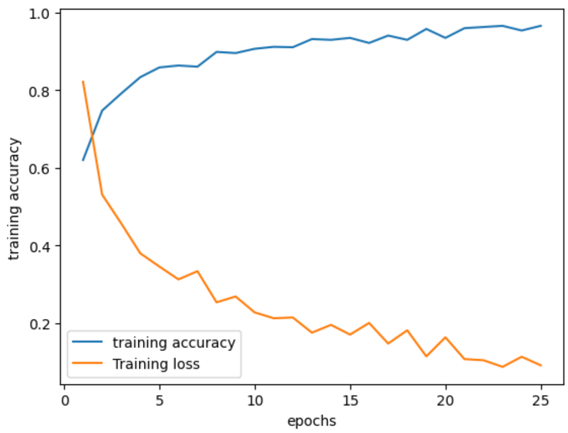
.A inception-resnet network architecture is used on the dataset,Inception-ResNet-v2 is a convolutional neural architecture that builds on the Inception family of architectures but incorporates residual connections (replacing the filter concatenation stage of the Inception architecture).convolutional filters are combined with residual connections.The network is 164 layers deep and can classify images into 1000 object categories.Efficient utilization of computing resource with minimal increase in computation load for the high-performance output of an Inception network.

VI. RESULTS

Validation accuracy



Training accuracy:



VII. CONCLUSIONS

In conclusion our proposed methodology is successful in detecting and discriminating melanoma lesions from non melanoma lesions.This aids medical professionals in early detection of melanoma and reducing fatality rate

VIII. REFERENCES

[1] K. Padmavathi, H. Neelam, M. P. K. Reddy, P. Yadlapalli, K. S. Veerella and K. Pampari, "Melanoma Detection Using Deep Learning," 2022 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2022, pp. 1-4, doi: 10.1109/ICCCI54379.2022.9741010.

[2] Cancer Statistics Center. (2019). American Cancer Society. [Online]. Available: https://cancerstatisticscenter.cancer.org

[3] C. Garbe, K. Peris, A. Hauschild, P. Saiag, M. Middleton, L. Bastholt, J.-J. Grob, J. Malvehy, J. Newton-Bishop, A. J. Stratigos, H. Pehamberger, and A. M. Eggermont, ‘‘Diagnosis and treatment of melanoma. European consensus-based interdisciplinary guideline—Update 2016,’’ Eur. J. Cancer, vol. 63, pp. 201–217, Aug. 2016.

[4] J. A. Curtin, J. Fridlyand, T. Kageshita, H. N. Patel, K. J. Busam, and H. Kutzner, ‘‘Distinct sets of genetic alterations in melanoma,’’ New England J. Med., vol. 353, no. 20, 2005, Art. no. 2135e47.

[5] J. A. Curtin, K. Busam, D. Pinkel, and B. C. Bastian, ‘‘Somatic activation of KIT in distinct subtypes of melanoma,’’ J. Clin Oncol., vol. 24, no. 26, pp. 4340–4346, Sep. 2006.

[6] H. Tsao, M. B. Atkins, and A. J. Sober, ‘‘Management of cutaneous melanoma,’’ New England J. Med., vol. 351, no. 10, 2004, Art. no. 998e1012.

[7] M. E. Celebi, H. A. Kingravi, B. Uddin, H. Iyatomi, Y. A. Aslandogan, W. V. Stoecker, and R. H. Moss, ‘‘A methodological approach to the classification of dermoscopy images,’’ Computerized Med. Imag. Graph., vol. 31, no. 6, pp. 362–373, Sep. 2007.

[8] G. Capdehourat, A. Corez, A. Bazzano, R. Alonso, and P. Musé, ‘‘Toward a combined tool to assist dermatologists in melanoma detection from dermoscopic images of pigmented skin lesions,’’ Pattern Recognit. Lett., vol. 32, no. 16, pp. 2187–2196, Dec. 2011.

[9] M. E. Celebi, H. Iyatomi, W. V. Stoecker, R. H. Moss, H. S. Rabinovitz, G. Argenziano, and H. P. Soyer, ‘‘Automatic detection of blue-white veil and related structures in dermoscopy images,’’ Computerized Med. Imag. Graph., vol. 32, no. 8, pp. 670–677, Dec. 2008.

[10] Q. Abbas, M. Celebi, C. Serrano, I. F. N. García, and G. Ma, ‘‘Pattern classification of dermoscopy images: A perceptually uniform model,’’ Pattern Recognit., vol. 46, no. 1, pp. 86–97, Jan. 2013.