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Research Article

Classification and Detection of Melanoma Skin Cancer Using Deep Learning Models

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Abstract

Melanoma, which means to "black tumor," is the most risky kind of skin cancer. It has the ability to spread to any region of the body and grows quickly. Melanomas cannot be treated if they are not discovered in their early stages. Thus, early detection is crucial for melanoma treatment. A neural network will be used to identify melanoma cancer.

Existing system use Neural Networks and Support Vector Machine to detect melanoma. The accuracy for Neural Network is 60%-75% and by using Support Vector Machine it is 80%. The main disadvantage of this model is no proper image preparation and the training takes a lot of time.

Keywords: Melanoma; Black Tumor; Skin Cancer

Introduction

Melanoma is a malignant cancer that is caused by pigment-containing cells called melanocytes. It has the fastest escalating death rate when it comes to skin cancers. People who spend time in the sun are exposed to UV light, which is the primary external factor that causes melanoma. The American Cancer Society predicts that there will be 7,230 melanomas-related fatalities in the US in 2019 in addition to 96,480 new cases of the illness. Cutaneous melanoma, the most lethal form of skin cancer, and the reason behind 90% of skin cancer-related deaths. Melanomas are responsible for 90% of mortality connected to cutaneous tumours (Garbe et al.). They also examined the incidence statistics, which show that there are roughly 25 new cases of melanoma per 100,000 people in Europe and 30 per 100,000 persons in the USA, and the highest incidence rate is reported in Australia, where there are almost sixty cases per 100,000 persons. Nonetheless, melanoma can be treated with prompt excision if it is identified when detected early enough. The identification of melanoma from skin lesions can be inaccurate and time-consuming, even with the assistance of experienced physicians. Visual inspection, clinical screening, biopsy, dermoscopic analysis, and histological examination of skin lesions are some of these methods. This is caused by the complicated visual characteristics of skin lesions, which include their variation in form, size, and fuzziness of the border. They also have the noise factors such skin hair , bubbles, and air are present. The development of an efficient Computer Aided Diagnosis (CAD) system is required for the identification and diagnosis of melanoma cancer. Melanoma diagnoses will rise as a result, and early detection will raise the possibility of successful treatment and reduce the disease's death rate.

Related works

The background study on the early detection of melanoma is explained here. Many methods have been developed to detectmelanoma.

Asymmetry in the ABCD rule refers to two sides that do not match for symmetry but match for the other. This helps us identify skinlesions that are benign or malignant. Whilemalignant skin lesions are destructive and cancerous, benign skin lesions do not pose a threat. Several manually developed techniques have traditionally used this criterion while analysing skin lesion photos in order todiagnose melanoma. The noise on the skin lesion, as well as the low contrast and uneven border aspects of the skin lesions, limit these so-called hand-crafted approaches. Thesetechniques lack thorough supervision, whichcauses a loss of specific information duringtraining and makes it challenging to analysethe intricate visual features of the skin lesion.

Codella et al. presented a system that builds ensembles of techniques that can segment skin lesions for melanoma identification by fusing cutting-edge advances in deep learningwith tried-and-true machine learning techniques. The complicated nature of skin lesion photos presents a number of hurdles to the skin cancer segmentation task, notwithstanding the significant success of those methods. Images of skin lesions are characterised by their irregular

sizes, hazy edges, and little contrast between the lesions and the background.

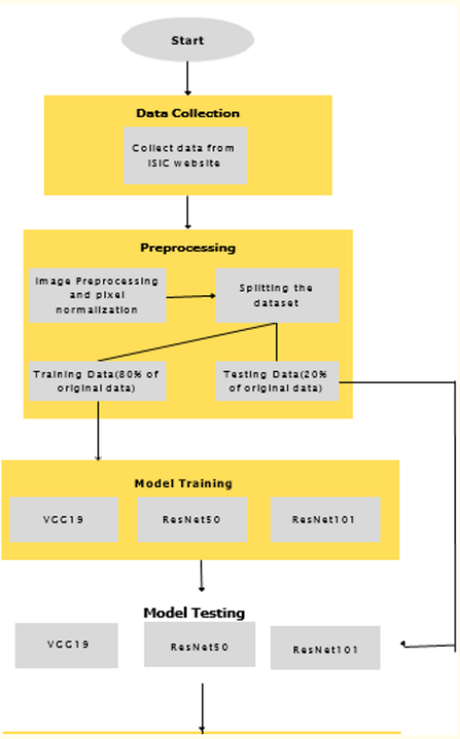
In 2014, Simoyan observed that the deeper Visual Geometry Group model (VGG) canguarantee a better efficacy in melanoma identification and that this architecture canfurther improve melanoma detection. This model is derived from learning models that employ a greater number of input picture descriptors (e.g., colour, symmetry, contour, etc.). The VGGs can also be applied to the search box itself, depending on the blocksand filter that are being utilised. The most popular models are VGG 11, 16, and 19, which have 8, 13, and 16 differentconvolutional layers, respectively, from one another.

The first architectures composed of Edge, Fog, and Cloud resources first surfaced in theIoMT framework in 2017. These layouts make anticipatory learning easier. Cloud- based methods make up the majority of IoMT data administration and analysis strategies described in the literature. Microdata centre mesh network nodes can be used to decentralise computing power for machine learning and deep learning techniques. This can lead to improvements in data archiving, diagnosis response times, resolution in medical image exchange, and individual user data security.

Methodology

In general, today's medical sectors rely onboth computer-aided diagnosis and a doctor's diagnosis. The lives of dermatologists and their patients are made easier by digital imageprocessing. Without making direct touch withthe skin, it assists in diagnosing the lesion area.

Detecting melanoma early is crucial because it's a deadly skin cancer compared to benign, which isn't as deadly, aiding in precise diagnosis for people and physicians. The project's objective is to distinguish between melanoma and non-melanoma lesions because it can be difficult to distinguish between the two because melanoma sometimes resembles benign lesions.



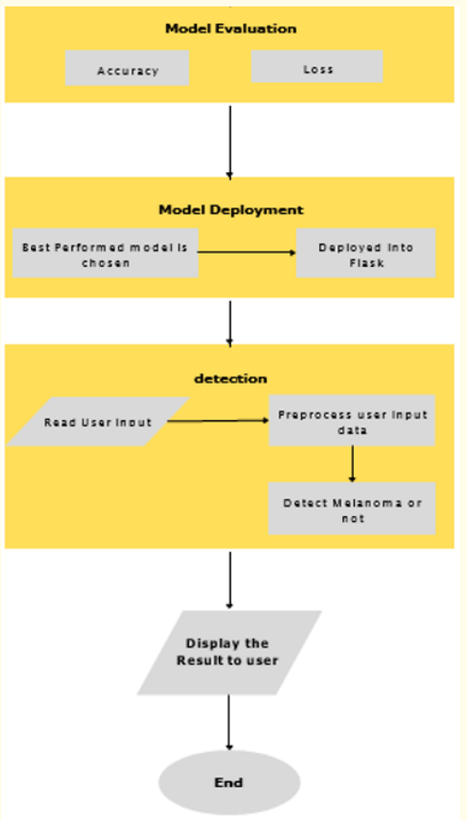


Figure 1: System Architecture.

The System Implementation section serves as a comprehensive guide to understanding the technical intricacies of our proposed system. It delineates the step-by-step process involved in implementing the system, encompassing.

- Data Collection
- Data Preprocessing
- Model Training
- Model Testing
- Model Evaluation
- Model Deployment
- Detection

Data collection

The dataset for melanoma skin cancer detection was obtained from the International Skin Imaging Collaboration (ISIC), a global effort to improve the diagnosis of melanoma and other skin diseases through the sharing of clinical and dermoscopic images. ISIC provides access to a diverse collection of annotated skin lesion images contributed by healthcare institutions, research organizations, and individual contributors worldwide.

Data preprocessing

Preprocessing is an important step in preparing data for deep learning models.

Initially, the images are resized to a uniform size to ensure consistency across the dataset, typically to the input size expected by thechosen models (e.g., 224x224 pixels). Next, the pixel values of the images are normalized to a range between 0 and 1 to facilitate faster convergence during training. Since thesemodels require images in RGB format, any grayscale images are converted to RGB.

Moreover, data augmentation techniques maybe applied, such as rotation, flipping, or zooming, to increase the diversity of the training dataset and improve the model's generalization ability.

Finally, the dataset is split into training and testing sets, ensuring that each set contains a balanced distribution of benign and malignant images to prevent class imbalance issues during model training. By performing these preprocessing steps, the input data iseffectively prepared to train deep learning models for melanoma skin cancer detection.

Model training

Model training is the process of teaching a deep learning model to recognize patterns and relationships in data so that it can make accurate predictions or classifications on new, unseen data.

In our project, we have utilised deep learning models – VGG19, RESNET50, RESNET101.

Visual geometry group (VGG19)

According to reports, the VGG-19 CNN architecture is capable of accuratelyanalysing large image datasets like ImageNet.The VGG-19 model, which was trained on 1.2 million general object pictures from 1,000different object categories in the ImageNetdataset, consists of over 143 millionparameters. The 19 trainable layers in the VGG-19 include convolutional and completely connected layers, max pooling, drop out, and fully connected layers.

Residual neural network (ResNet- 50)

This architecture gave rise to the concept of Residual Blocks, which addresses the vanishing/exploding gradient problem. With this network, we use a technique called skip connections. To connect layer activations to later layers, the skip connection skips acrossa few levels. ResNets are constructed by stacking these residual pieces.ResNet-50 is a 50-layer deep convolutional neural network made up of 1 average pool layer, 1 maxPool layer, and 48 convolutional layers. By stacking leftover blocks, a specific type ofartificial neural network known as a residual neural network builds a network. A pre- trained version of the network, trained on more than a million photographs, will be loaded using the ImageNet database. 1000distinct object kinds can be used to classify images using a network.

Residual Neural Network (ResNet- 101)

ResNet-101 is a 101-layer convolutionalneural network that is a modified version of the 50-layer ResNet. A pre-trained version of the network, trained on over a million photographs, is stored in the ImageNet database. The pretrained network can identify1000 distinct object categories from images, such as diverse animals, a mouse, a pencil, and a keyboard. Consequently,comprehensive feature representations for a large variety of pictures are now included in the network. The network supports images upto 224 by 224 in resolution.

Model testing

Model testing is a crucial step in evaluating the performance and generalization ability of a trained deep learning model on unseen data. The separate test dataset that was not used during model training is used in testingthe models. Trained deep learning models are loaded to evaluate. Test data (20%) is chosen to test the models. Used the trained model to make forecasting on the test dataset.

Model evaluation

Model evaluation in deep learning involves assessing the performance of trained models using various metrics such as accuracy and loss. We typically compute the accuracy and loss metrics using the following formulas:

Accuracy

The percentage of correctly identified samples relative to the total number ofsamples is known as accuracy. It is calculatedas follows:

$$Accuracy = \frac{Number\ of\ Correctly\ Classified\ Samples}{Total\ Number\ of\ Samples}$$

Loss

The difference between the model'santicipated outputs and the actual ground truth labels is measured by a metric called loss. It measures the model's effectiveness. For multi-class classification

$$Loss = \frac{1}{N}\sum_{i=1}^{N} L(y_i, \hat{y}_i)$$

Where:

- N is the total number of samples in the dataset.
- L is the loss function.
- y_i is the true label of the i^{th} sample.
- $\hat{y}_i$ is the predicted label of the i^{th} sample.

tasks, binary cross-entropy is a common loss function, and for binary classification tasks, categorical cross-entropy. The average of the losses across all samples in the dataset is used to calculate the loss.

Model deployment

Deploying a deep learning model into a Flaskweb application involves the process ofmaking the model accessible via an API (Application Programming Interface) so thatit can receive input data, make predictions, and return results to the client application.

Detection

Detection, is the final step in a project, involves using a trained deep learningmodel to predict the given image is melanoma or not.

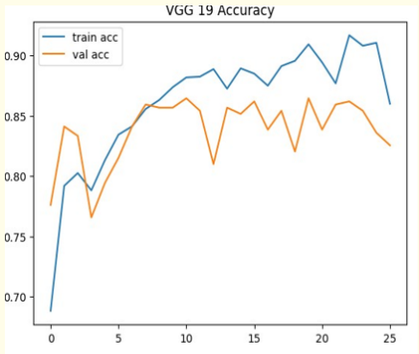


Figure 2: VGG 19 Accuracy Graph.

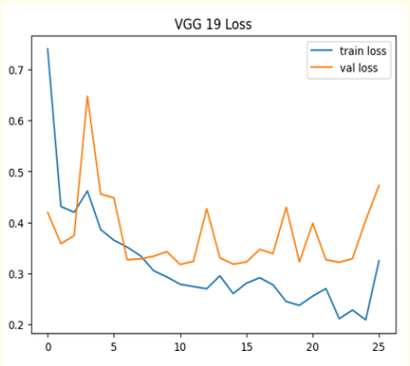


Figure 3: VGG 19 Loss Graph.

VGG – 19

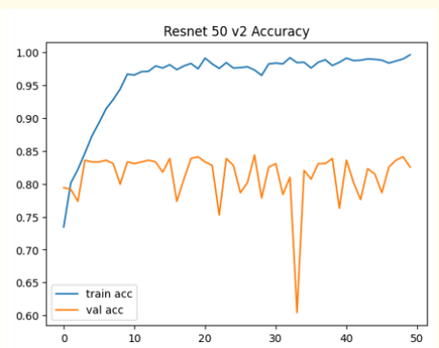


Figure 4: VGG 19 Loss Graph.

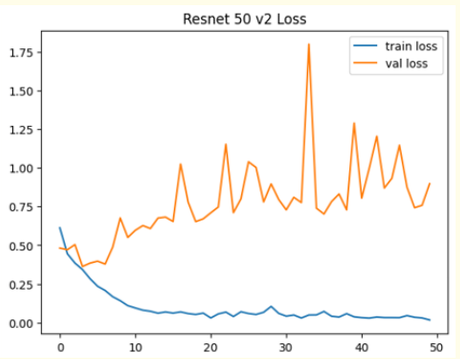


Figure 5: RESNET - 50 Loss Graph.

RESNET – 50

Accuracy score comparisons

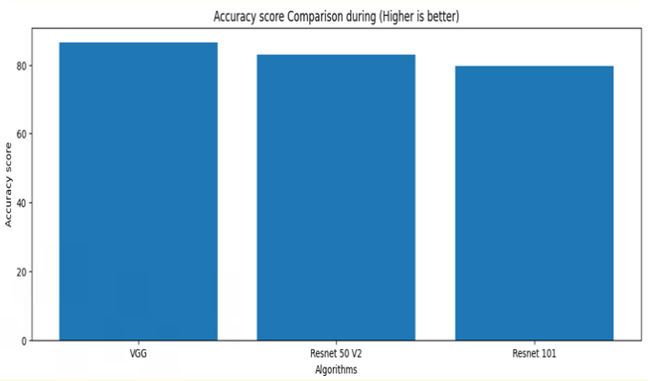


Figure 6: RESNET - 101 Accuracy Graph.

[86.50000095367432, 82.99999833106995, 79.75000143051147].

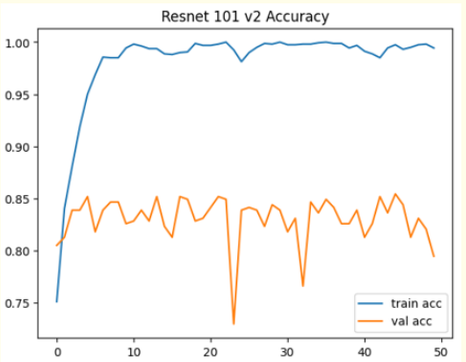


Figure 7: RESNET - 101 Loss Graph.

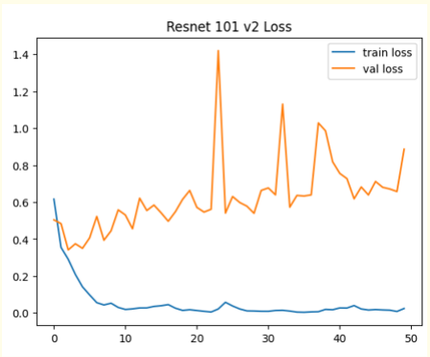


Figure 8: Accuracy Comparison.

Text(0.5, 1.0, 'Accuracy score Comparison during (Higher is better)').

RESNET – 101

Conclusion

In our project we uses deep learning approaches to identify melanoma cancer using deep convolutional neural networks with three alternative strategies. Themodel is trained using VGG-19, which has 19 convolutional layers and an 86% accuracy rate, in

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