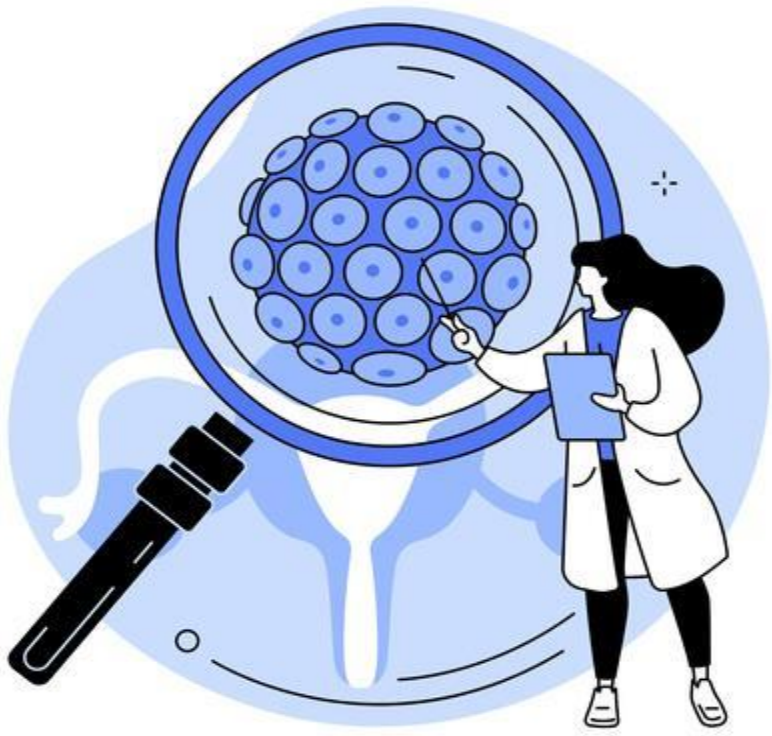


Melanoma Skin Cancer detection using Machine Learning

Bhanu Pratap Agarwal, Akshat Singhania, Daksh Jain, Shreshth Mangal

Inspiration

Computer systems now have a direct or indirect influence on practically every application in the world. Computers are employed in a variety of fields for automated applications. Identifying the disease at an early stage is critical for improved treatment and cure in diseases such as cancer. Many individuals throughout the world are suffering from skin illnesses, and the incidence of skin cancer cases is higher than any other type of cancer. not all skin cancers are lethal, it is necessary to anticipate if it is a deadly cancer or not by looking at skin photos. Melanoma accounts for only 5% of all skin malignancies, yet it is fatal 75% of the time, according to the American Cancer Society. Detecting skin cancer by human doctors necessitates more expertise and information, and as the number of skin cancer cases increases, so does the number of professionals who can correctly diagnose the condition. Because it is difficult to find more human specialists, many researchers are now working on building machine learning algorithms to overcome this problem. The automated identification of skin cancer is a difficult task, but by teaching the computer, it can determine whether or not the skin is affected with lethal cancer. This research presents a Deep Learning technique to cancer prediction. The suggested method was implemented with Resnet and vgg16 models tested on a standard cancer dataset, with an accuracy of more than 85%.

There has recently been a lot of interest in developing Artificial Intelligence (AI) enabled computer-aided diagnostics solutions for skin cancer diagnosis. With the rising prevalence of skin malignancies, a lack of awareness among a growing population, and a lack of competent clinical competence and resources, there is an urgent need for AI systems to support doctors in this sector. A huge amount of skin lesion datasets are publically available, and researchers have created AI solutions, notably deep learning algorithms, to differentiate malignant from benign skin lesions in several picture modalities such as dermoscopic, clinical, and histopathological images.

Skin cancer diagnosis is now achievable because of advances in picture pre-processing and machine learning approaches. Convolutional Neural Network is a well-known and widely used approach (CNN). Following dermoscopic image segmentation, the features of the damaged skin cells are extracted using the feature extraction technique. We present a convolutional neural network model for detecting cancerous skin conditions and classifying them as malignant (melanoma) or benign (non-malignant). The architecture of the aforementioned model has several layers that aid in computer reading of the dataset. In these situations, accurate outcomes are always expected. To avoid errors, we are taking a manual approach rather than an automatic one.

A human eye can easily separate photos of similar look, but classifying photographs such as those of cancer-affected skin requires more knowledge. And, as the number of skin cancer cases increases globally, more human experts are needed. To address this issue, numerous researchers are developing machine

learning classifiers that can identify skin cancer automatically by classifying skin photos. This research focuses on creating a method for predicting skin cancer by classifying photos with a deep convolutional neural network. The suggested method has been tested on a conventional cancer dataset and has achieved greater than 85% accuracy.

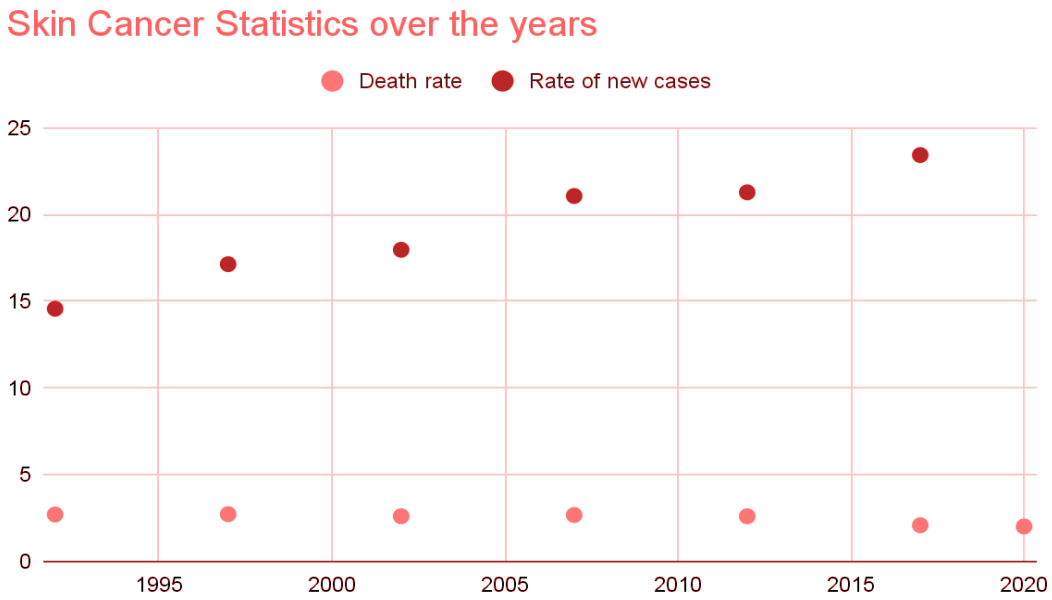
As skin cancer is becoming more prevalent, there has been a significant loss of life. There is no problem if it is caught early. If it is diagnosed during the peak stages, the chance of survival lowers from 99% to 14%. Different procedures were used to identify cancer early, but some yielded good results while others did not, and they were uncomfortable. The accuracy of detection should improve so that malignant skin can be recognised early and treated properly. Deep Learning offers various models that can be used to overcome less accurate methods.

Overview

Skin cancer is regarded as one of the most dangerous types of cancer, with a significant increase in deaths due to a lack of knowledge about the symptoms and their prevention. Thus, early detection at an early stage is required to prevent cancer from spreading. Skin cancer is further classified into several types, the most dangerous of which are Melanoma, Basal cell carcinoma, and Squamous cell carcinoma. The goal of this project is to detect and classify malignant(least harmful cancer) and benign(lethal cancer) machine learning and image processing tools. Dermoscopic images are used as input in the pre-processing stage. Because colour is an important factor in determining the type of cancer, colour-based clustering is used during the segmentation phase.

Skin Cancer is categorised in Melanoma and Nonmelanoma. (MSC) is the most dangerous type of skin cancer. It can be successfully treated with surgical techniques if detected early. However, once metastasis(the spread of cancer cells from the place where they first formed to another part of the body) occurs, survival rates are considerably lowered. Melanoma diagnosis is based on clinical examination and classic features on lesion biopsy. Basal cell carcinoma (NMSC) and squamous cell carcinoma are two types of NMSC. The success of skin cancer hinges on early detection and treatment. Visual examination may not be enough to distinguish benign lesions from malignant malignancies. Histopathology evaluation of the skin sample is the gold standard approach. Some of the disadvantages of skin biopsy include the intrusive nature of the technique, associated pain, and the necessity for repeated samples in suspected lesions with varying presentations.

Our working prototype can detect Melanoma and Basal cell carcinoma.



Melanoma and Basal Cell Carcinoma

Melanoma is an abbreviation for "black tumour." It spreads swiftly and can infiltrate any organ (metastasis). Melanoma is caused by melanocytes, which are skin cells. These cells are responsible for the production of melanin, the dark pigment that gives skin its colour. The majority of melanomas are black or brown in hue. About 30% of melanomas develop in pre-existing moles, whereas the remainder begin in normal skin. Knowing your risk might help you be more careful in monitoring changes in your skin and obtaining skin tests, as melanomas have a 99% cure rate if detected early. The depth of the malignant development is closely related to treatment outcome, thus early detection is critical. Melanoma incidence has skyrocketed in the last 30 years. You can get melanoma in any area of your body. Melanoma can even form on your eyes and internal organs. Men are more prone to develop melanoma on their trunk — often the upper back. Women are more likely to have melanoma on their legs.

Basal cell carcinoma (BCC) is the most frequent type of skin cancer as well as the most common type of cancer in general. In the United States alone, an estimated 3.6 million cases are diagnosed each year. BCCs are caused by abnormal and unregulated basal cell growth. BCCs are curable and cause little harm if found and treated early since they develop slowly. Understanding the causes, risk factors, and symptoms of BCC will help you recognise it early, when it is simplest to treat and cure. Basal cell carcinoma is a type of skin cancer that develops on exposed areas of your skin. It's natural to be concerned when your doctor diagnoses you with it, but bear in mind that it's the least dangerous sort of skin cancer. You can be treated if you catch it early. This

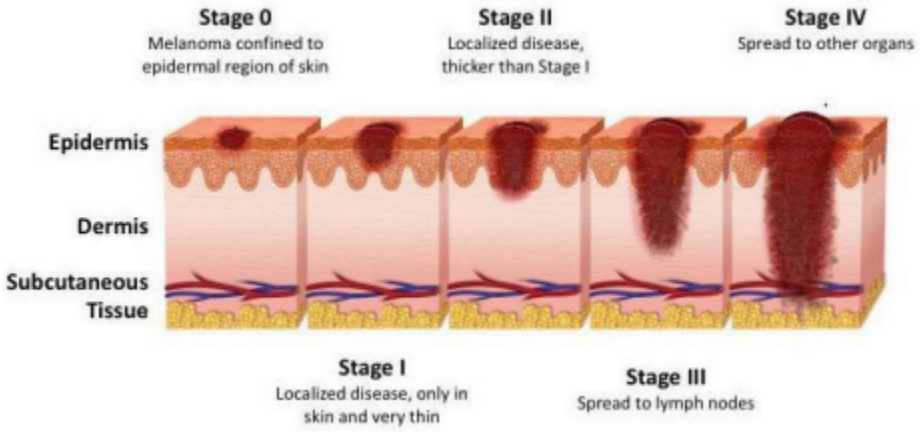
cancer is unlikely to migrate from your skin to the rest of your body, although it may expand nearby into bone or other tissue beneath your skin. Several treatments are available to prevent this from occurring and to eradicate the malignancy.

Most experts agree that excessive sun exposure, particularly sunburns while you are young, is a key risk factor for melanoma. According to statistics, solar ultraviolet (UV) rays cause 86% of melanomas. UV rays can damage a cell's DNA, causing alterations to specific genes that regulate how cells grow and divide. When your skin's DNA is broken and cells begin to reproduce, problems can arise. UV radiation from tanning beds (a device that generates ultraviolet radiation to give individuals a tan) also enhances the incidence of melanoma and has been identified by the World Health Organization as a carcinogen (cancer-causing substance).

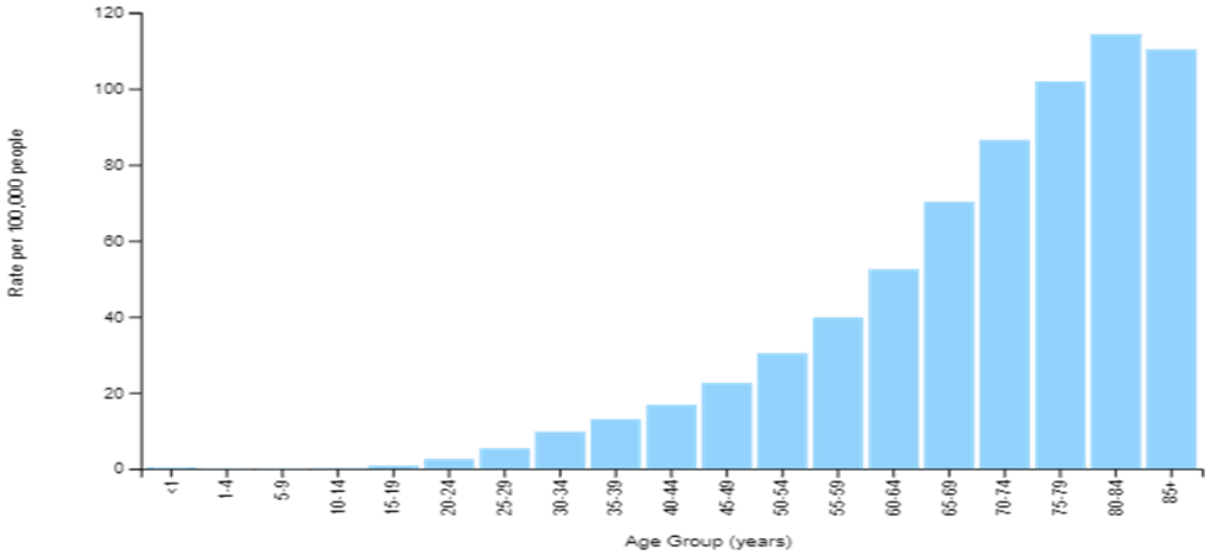
Although anybody can acquire skin cancer, those with the following risk factors are more likely to develop the disease:

- Melanoma runs in the family.
- Fair skin, freckles, blond or red hair, and blue eyes are all characteristics.
- Excessive sun exposure, including sunburns.
- A residence near the equator or at high altitudes - residing in these areas may increase your UV exposure.
- A history of using tanning beds.
- Many moles, particularly unusual moles
- A compromised immune system.

The primary detection is a biopsy. It is the removal of some cells or tissue, fluids or growths for examination. The sample can be taken from any part of your body. It's sent to a laboratory for testing and is looked at under a microscope. Moreover, a CT scan can show if melanoma is in your internal organs. Adding on, an MRI scan is used to check for melanoma tumours in the brain or spinal cord. Lastly, a PET scan can check for melanoma in lymph nodes and other parts of your body distant from the original melanoma skin spot.



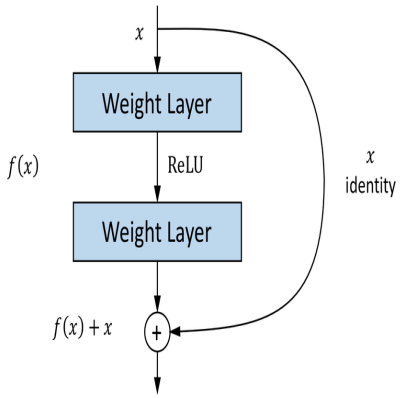
The Rate of Melanoma per 100,000 people in terms of age



Background:

ResNet

Deeper neural networks are more difficult to train. A residual learning framework is easy to train. The layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions are explicitly reformulated. It has been shown that residual networks are easier to optimise, and can gain accuracy from considerably increased depth. Residual nets (ResNets) are with a depth of up to 152 layers, i.e., x8 deeper than e.g. VGG nets but still having lower complexity.



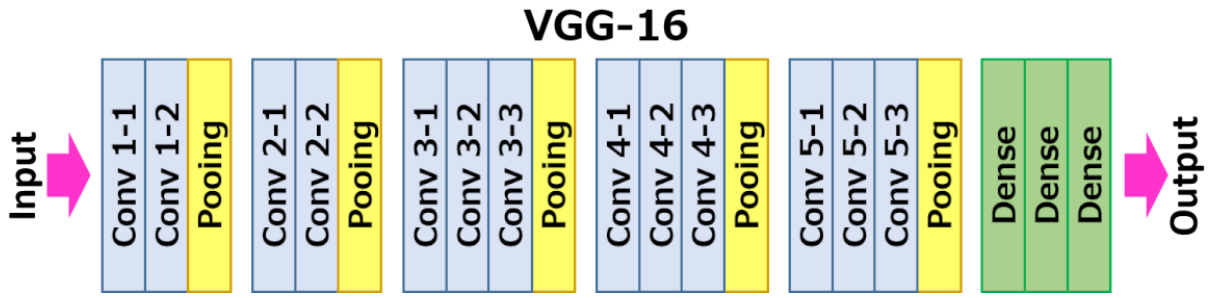
Residual learning: a building block.

The degradation (of training accuracy) indicates that not all systems are similarly easy to optimise. The degradation problem is addressed by introducing a deep residual learning framework. Instead of hoping each few stacked layers directly fit a desired underlying mapping, we explicitly let these layers fit a residual mapping. Formally, denoting the desired underlying mapping as H(x), we let the stacked nonlinear layers fit another mapping of F(x) := H(x)−x. The original mapping is recast into F(x)+x. We hypothesise that it is easier to optimise the residual mapping than to optimise the original, unreferenced mapping. To the extreme, if an identity mapping were optimal, it would be easier to push the residual to zero than to fit an identity mapping by a stack of nonlinear layers.

The formulation of F(x)+x can be realised by feedforward neural networks with ''shortcut connections'' (see scheme). Shortcut connections are those skipping one or more layers. In our case, the shortcut connections simply perform identity mapping, and their outputs are added to the outputs of the stacked layers (see scheme). Identity shortcut connections add neither extra parameter nor computational complexity. The entire network can still be trained end-to-end by SGD with backpropagation, and can be easily implemented using common libraries

VGG16

VGG16 (also called OxfordNet) is a convolutional neural network architecture named after the Visual Geometry Group from Oxford, who developed it.... By only keeping the convolutional modules, our model can be adapted to arbitrary input sizes. The model loads a set of weights pre-trained on ImageNet.



Theory:

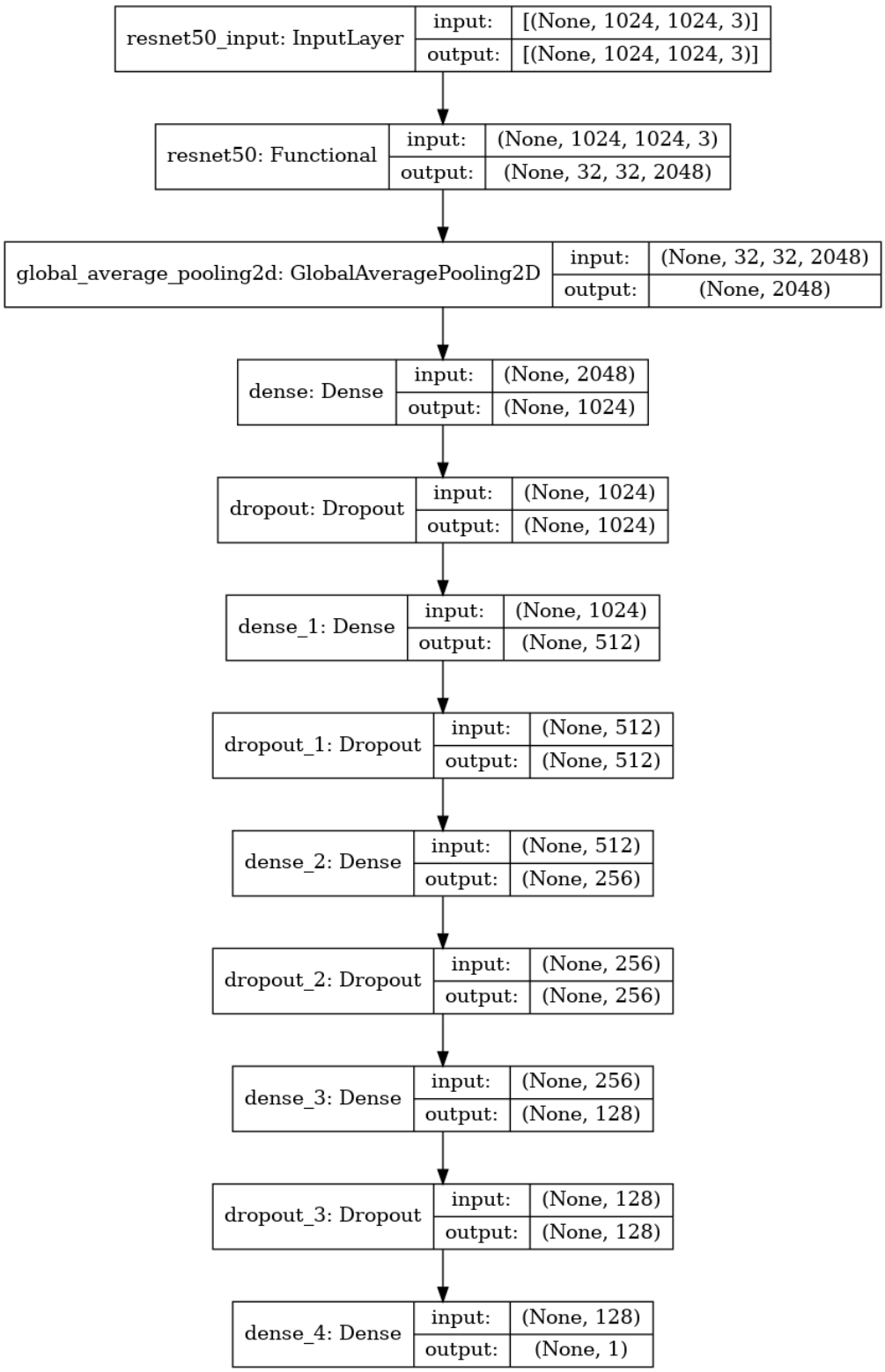
There are various techniques in image processing for image classification. Deep convolutional neural network (CNN) is a new approach for this problem. Researchers are using this technique recently in various classification problems. Deep learning models are used in many application areas of medicine. Early detection saves the life of many patients in cancer diseases and the detection of skin lesions is proposed all over the world. The proposed methodology was tested on an ISIC dataset and found to be accurate. Skin cancer cases are increasing day by day and presently they are more in number compared to any other type of cancer in the US.

We tried to create CNN sequential models with different configurations of hidden layers but it was simply not sophisticated enough to handle the minute details of the text of skin texture so we used preexisting image classifications models.

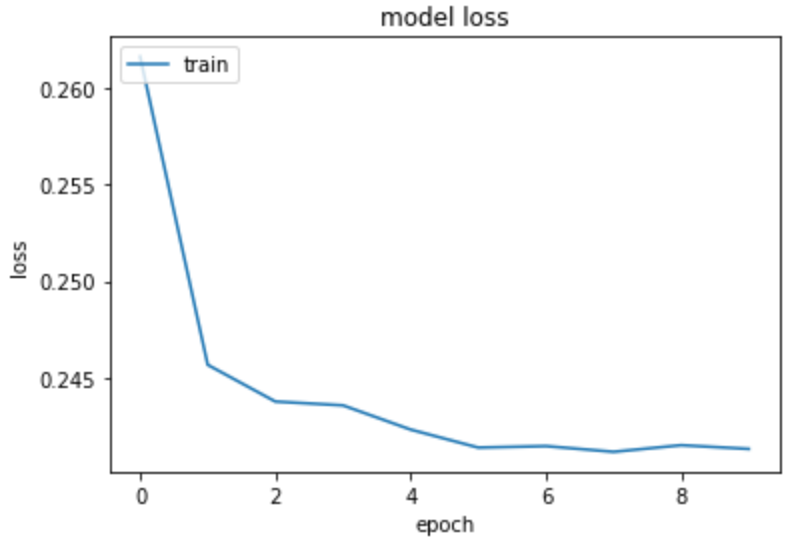
The dataset was first obtained, then the images were assigned to train and test images, then the train and test images were combined, and then multiple deep learning processes, such as RESNET-50, were applied to the dataset. The findings will then be provided by the compiled data.

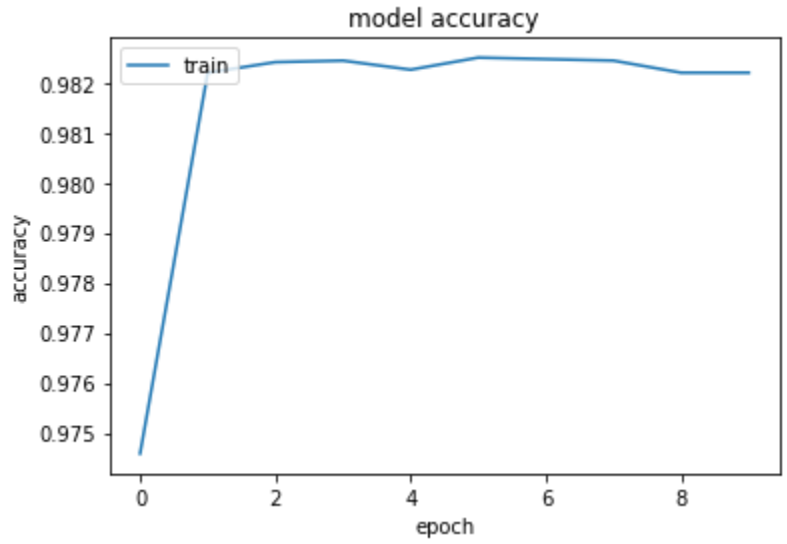
Both VGG16 and InceptionV3 algorithms assess the classification performance. We achieved two experiments using the same described dataset. We conducted both the training using the ISIC dataset , which had images and the given skin cancer type.We predicted the chances of melanoma with over 85% accuracy. The performances of the modified VGG16 model are compared to three state of the art methods labelled as

It is clear that our proposed method gave good results. However, there is a need to improve its performances in our future work. In fact, merging or concatenating deep learning models could improve the classification


resnet50_input: InputLayer
input: [(None, 1024, 1024, 3)]
output: [(None, 1024, 1024, 3)]
resnet50: Functional
input: (None, 1024, 1024, 3)
output: (None, 32, 32, 2048)
global_average_pooling2d: GlobalAveragePooling2D
input: (None, 32, 32, 2048)
output: (None, 2048)
dense: Dense
input: (None, 2048)
output: (None, 1024)
dropout: Dropout
input: (None, 1024)
output: (None, 1024)
dense_1: Dense
input: (None, 1024)
output: (None, 512)
dropout_1: Dropout
input: (None, 512)
output: (None, 512)
dense_2: Dense
input: (None, 512)
output: (None, 256)
dropout_2: Dropout
input: (None, 256)
output: (None, 256)
dense_3: Dense
input: (None, 256)
output: (None, 128)
dropout_3: Dropout
input: (None, 128)
output: (None, 128)
dense_4: Dense
input: (None, 128)
output: (None, 1)

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Functional)        (None, 32, 32, 2048)      23587712
_________________________________________________________________
global_average_pooling2d (Gl (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 1024)              2098176
_________________________________________________________________
dropout (Dropout)            (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               524800
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               131328
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_3 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 129
=================================================================
Total params: 26,375,041
Trainable params: 26,321,921
Non-trainable params: 53,120
_________________________________________________________________
```

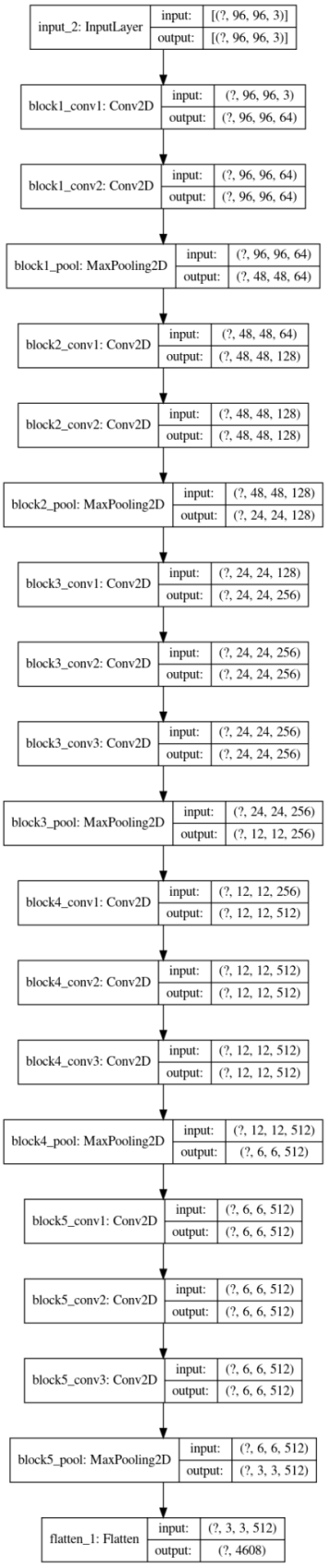




We have 26 million training parameters and 53,000 pre-trained parameters, the pre-trained weights are from imagenet module for resnet50 which is very effective in classifying images.

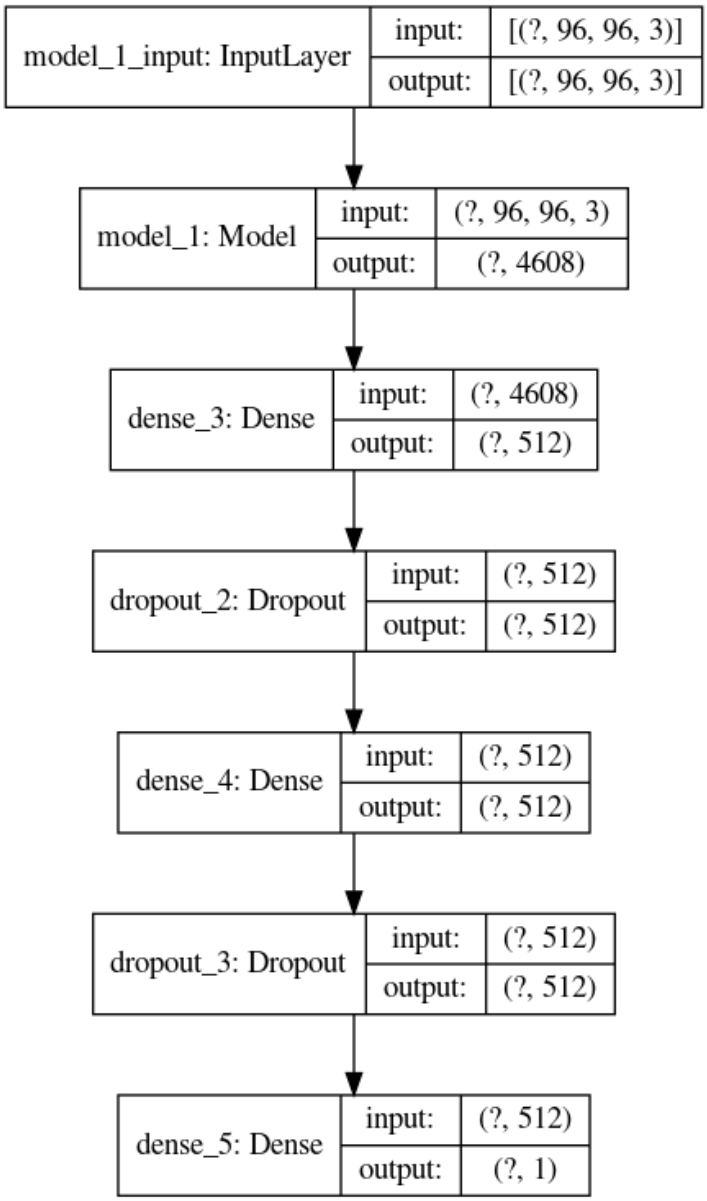
We achieved a test accuracy of 98.64 test accuracy

Using VGG16 ~


input_2: InputLayer
input: [(?, 96, 96, 3)]
output: [(?, 96, 96, 3)]
block1_conv1: Conv2D
input: (?, 96, 96, 3)
output: (?, 96, 96, 64)
block1_conv2: Conv2D
input: (?, 96, 96, 64)
output: (?, 96, 96, 64)
block1_pool: MaxPooling2D
input: (?, 96, 96, 64)
output: (?, 48, 48, 64)
block2_conv1: Conv2D
input: (?, 48, 48, 64)
output: (?, 48, 48, 128)
block2_conv2: Conv2D
input: (?, 48, 48, 128)
output: (?, 48, 48, 128)
block2_pool: MaxPooling2D
input: (?, 48, 48, 128)
output: (?, 24, 24, 128)
block3_conv1: Conv2D
input: (?, 24, 24, 128)
output: (?, 24, 24, 256)
block3_conv2: Conv2D
input: (?, 24, 24, 256)
output: (?, 24, 24, 256)
block3_conv3: Conv2D
input: (?, 24, 24, 256)
output: (?, 24, 24, 256)
block3_pool: MaxPooling2D
input: (?, 24, 24, 256)
output: (?, 12, 12, 256)
block4_conv1: Conv2D
input: (?, 12, 12, 256)
output: (?, 12, 12, 512)
block4_conv2: Conv2D
input: (?, 12, 12, 512)
output: (?, 12, 12, 512)
block4_conv3: Conv2D
input: (?, 12, 12, 512)
output: (?, 12, 12, 512)
block4_pool: MaxPooling2D
input: (?, 12, 12, 512)
output: (?, 6, 6, 512)
block5_conv1: Conv2D
input: (?, 6, 6, 512)
output: (?, 6, 6, 512)
block5_conv2: Conv2D
input: (?, 6, 6, 512)
output: (?, 6, 6, 512)
block5_conv3: Conv2D
input: (?, 6, 6, 512)
output: (?, 6, 6, 512)
block5_pool: MaxPooling2D
input: (?, 6, 6, 512)
output: (?, 3, 3, 512)
flatten_1: Flatten
input: (?, 3, 3, 512)
output: (?, 4608)

^ The VGG16 Model we are using

The sequential model implementation



We were able to achieve a test accuracy of `84.92% and and loss of 49.9% using the model`

In this section, we present and discuss the obtained classification results when both proposed models are used. accuracy and loss metrics are considered for performance evaluation of proposed classifiers. We used

Binary_crossentropy as the loss function .

$$H(P^*|P) = -\sum_i \underbrace{P^*(i)}_{\text{TRUE CLASS DISTIRBUTION}} \log \underbrace{P(i)}_{\text{PREDICTED CLASS DISTIRBUTION}}$$

And Adam for the optimizer

This algorithm is used to accelerate the gradient descent algorithm by taking into consideration the 'exponentially weighted average' of the gradients. Using averages makes the algorithm converge towards the minima in a faster pace.

$$w_{t+1} = w_t - \alpha m_t$$

$$m_t = \beta m_{t-1} + (1-\beta)\left[\frac{\delta L}{\delta w_t}\right]$$

Where,

mt = aggregate of gradients at time t [current] (initially, mt = 0)

mt-1 = aggregate of gradients at time t-1 [previous]

Wt = weights at time t

Wt+1 = weights at time t+1

αt = learning rate at time t

∂L = derivative of Loss Function

∂Wt = derivative of weights at time t

β = Moving average parameter (const, 0.9)mt = aggregate of gradients at time t [current] (initially, mt = 0)

Conclusion

One of the most important factors for appropriate therapy is detecting skin cancer in its early stages. In reality, any sort of cancer is the same. It is difficult to diagnose cancer in its early stages before a tumour or structural alteration appears. As a medical procedure, biopsy might be used. However, in today's technologically advanced world, it is possible to use algorithms and datasets with machine-aided support. Our methodology assists clinicians in recognising patients as soon as possible. This deep learning model of skin cancer diagnosis using Convolutional Neural Network can be utilised to help clinicians in addition to their experience. For future work, we can develop a mobile (Android/iOS) or web-based deep learning framework where we can upload our image and validate the output, which can be more reliable, fast, and affordable than the existing method.

We suggest two modified models for skin cancer classification in this paper: modified VGG16 and Resnet models. The application of data augmentation demonstrated that reducing data imbalance can be effective in improving classification performance, but careful tuning is required; for example, training with perfectly balanced data does not always result in a better model. Performance is measured using many metrics like accuracy. Two experiments are carried out. We considered melanoma mainly and basal cell carcinoma. The experiments revealed that the Resnet is a reliable multiple classifier that outperforms the model VGG16. For accuracy, compared to state of the art considered methods, results showed that better accuracy values are obtained for binary classification using a modified Resnet50 model.

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architecture visualisation
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