CNN for Skin Cancer Detection and Diagnosis

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***Abstract*—Skin cancer is the most prevalent kind of cancer . Because of skin cancer's quick growth rate, high treatment costs, and high fatality rate, early identification has become increasingly important. This study uses deep neural networks and transfer learning architecture to create an artificial skin cancer diagnosis system. We trained and tested our models using the publicly accessible processed skin cancer images from the ISIC Archive. The accuracy was 0.920, precision was 0.91, recall was 0.91, F1 score was 0.91, and the ROC-AUC was 0.914.**

***Index Terms*—Skin cancer, Deep neural networks, Transfer learning**

I. Introduction

Skin cancer is the most commonly diagnosed cancer in both men and women, according to statistics. It is prevalent not just in underdeveloped nations, but also in developed countries. Overexposure to sunlight is the leading cause of skin cancer, especially when it results in sunburn and blistering. The sun's ultraviolet (UV) rays destroy your skin's DNA, causing abnormal cells to grow. These abnormal cells divide fast and in a disorganized fashion, resulting in a mass of cancer cells. A change in your skin, either a new growth or a change in an existing growth or mole, is the most typical warning sign of skin cancer.

Doctors have traditionally detected skin cancer with their naked eye. However, because humans make mistakes, this often leads to a less accurate detection. This is where computer vision comes in to help automate the entire process.

Deep neural network models can be used to train images of both the categories (benign and malignant). The model can determine if a new image is in the benign or malignant class by learning the non linear interactions.

Part II discusses prior studies on skin cancer detection, followed by a discussion of the proposed methodology in section III. The skin-cancer system's results and conclusion are discussed in sections IV and V, respectively.

II. Related Works

Deep learning algorithms have shown promising results in a variety of fields and applications, such as natural language processing, speech recognition, etc. There has been a lot of researches done and published in the domain of skin cancer classification using computer vision and deep learning algorithms.

In [1], the authors have done multi-class classification with classes named as Healthy, Acne, Eczema, Benign and Malignant. Using two separate algorithms, Support Vector Machine (SVM) and CNN, they were able to achieve an accuracy of around 86%

In [2], the authors proposed a closed elastic curve methodology combined with an intensity threshold method for correctly detecting the skin lesion boundaries.

The authors of [3] presented a technique for detecting hazardous melanoma skin malignant development by eliminating distinctive highlights using a 2D wavelet transformation. The generated image is then delivered as a contribution to the fake neural system classifier. However, the procedure's drawback is that it can only discriminate outcomes to an accuracy level of 84%

III. Methodology

Computer vision can be used to categorise various lesions based on the image's attributes. Deep Learning is used to figure out what structures are unknown in the input data. In our project, we made computers to analyse images using computer vision, and then employed CNN algorithms to evaluate and forecast the results. Fig.1 shows the workflow of the proposed model.

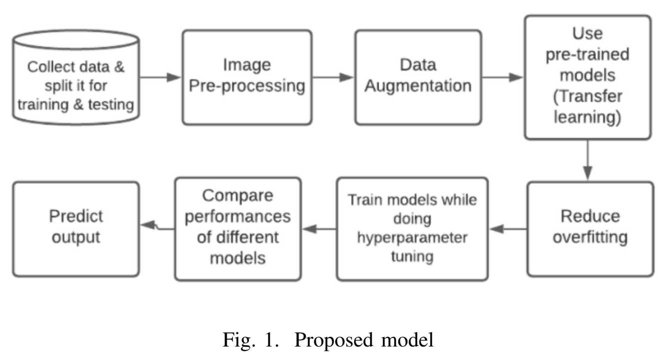

Fig. 1. Proposed model

A. Data-set Description

We got the data from the ISIC website. We used 2637 images for training and 660 images for testing of size 224 × 224. Fig.2 shows a sample of the data-set.

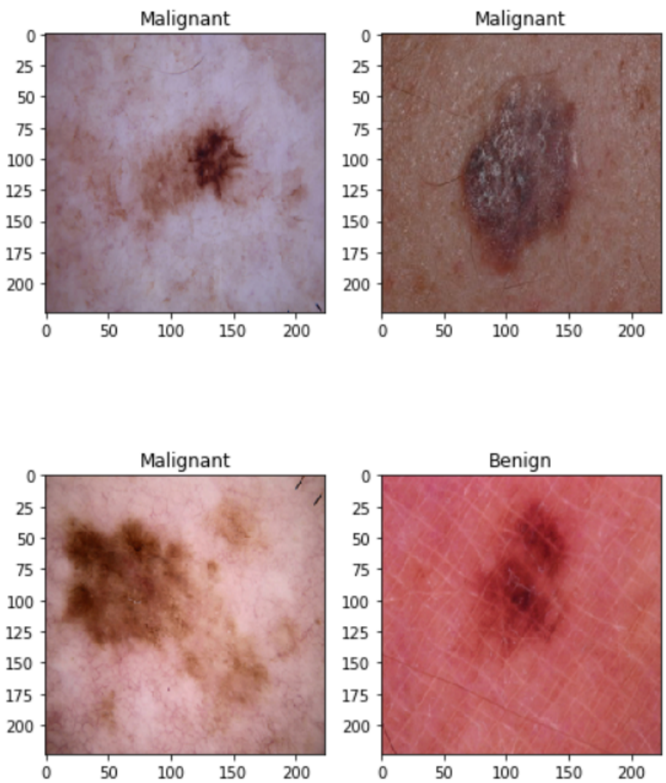

Fig. 2. Data-set sample

B. Image Pre-processing

- Re-sizing: The scaling of pictures is referred to as image resizing. It helps in the reduction of the number of pixels in an image, which has various advantages, for example, I It can shorten the time it takes to train a neural network since the more pixels in an image there are, the more input nodes there are, which raises the model's complexity.
- Inpainting: Inpainting is the process of recovering a picture that has been damaged owing to a variety of processes such as noise reduction, hair removal, resizing, and so on. This approach is useful for recovering picture elements that have been lost or damaged.
- Normalization: It is the transformation of a picture into an array. The pixel values are changed from 0 to 255 to 0 and 1.

  The pre-processed picture will then be sent into a classifier that uses a skin cancer model to classify it. The CNN classifier is utilised in our study to do classification between the two types of images: benign and malignant. The user will be given the output of the kind of lesion based on the likelihood estimated using the softmax activation function.

C. Convolution Neural Networks (CNN)

A convolutional neural network (CNN) is a form of artificial neural network that is specifically built to handle pixel input and is used in image recognition and processing. Convolution, maxpooling, and activation function are the three main components of CNNs.

In a traditional neural network, each layer is made up of a group of neurons, and each layer's neuron is linked to the neurons of the layer before it, however hidden layers in CNN have a slightly different design. A layer's neurons are not entirely connected to the previous layer's neurons; rather, they are only connected to a limited number of neurons from the prior layer. Translation-invariant features are achieved by restricting connections to local connections and adding extra pooling layers that aggregate local neuron outputs into a single value. Because there are fewer parameters and the model complexity is smaller, the training approach is simpler.

D. Transfer Learning

For the categorization, we applied the concept of transfer learning. Transfer learning is the process of applying a previously learnt model to a new problem. It is commonly used in computer vision and natural language processing applications like sentiment analysis due to the enormous amount of CPU resources required. Neural networks in computer vision often try to identify edges in the first layer, shapes in the intermediate layer, and task-specific characteristics in the latter layers. Transfer learning uses the early and central layers, whereas the subsequent layers are just retrained. It uses the labelled data from the task on which it was trained.

For our project, we employed three pre-trained models: Inception-v3, InceptionResNet-v2, and ResNet-50 as pre-trained weights.

a) Inception-v3: Inception-v3 is a 48-layer deep pre-trained convolutional neural network model. It's a version of the network that's already been trained on over a million photos from the ImageNet data-set [4]. It was fine-tuned across all layers and replaced top layers with one average pooling, two completely connected, and lastly the softmax layer, allowing it to categorise two diagnostic categories on our dataset. To be compatible with this model, all input photos were resized to (224, 224). Adam was used as the optimizer, and the learning rate was set to 0.0001.

b) InceptionResNet-v2: This 164-layer network can identify photos into 1000 item categories, including keyboards, mice, pencils, and a variety of animals. It was fine-tuned across all layers and replaced top layers with one average pooling, two completely connected, and lastly the softmax layer, allowing it to categorise two diagnostic categories on our data-set. To be compatible with this model, all input photos were resized to (224, 224). Adam was used as the optimizer, and the learning rate was set to 0.0001.

c) ResNet-50: ResNet-50 is a 50-layer deep convolutional neural network. The network's image input size is 224 × 224 pixels. Adam was used as the optimizer, and the learning rate was set to 0.0001. The inputs are mapped using identity mapping. This identity mapping has no parameters and serves just to add the output from the previous layer to the next layer. To expand the shortcut channels to fit the residual, the identity mapping is multiplied by a linear projection. The Skip Connections between layers feature adds prior layer outputs to stacked layer outputs. As a result, it is now feasible to train considerably deeper networks than what was previously achievable.

IV. Experimental Evaluation

The next step after implementing deep learning models is to assess the model's efficacy using metrics and data sets. The classifier's loss vs. epochs, accuracy vs. epochs, confusion matrix, and ROC-AUC curve were all plotted as shown in the below figures.

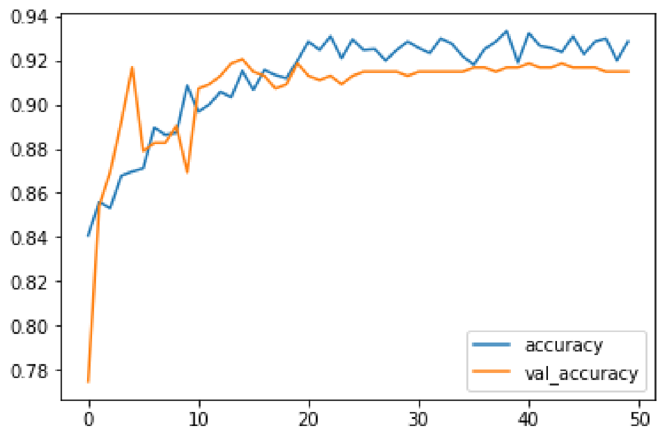

Fig. 3. Accuracy vs Epoch

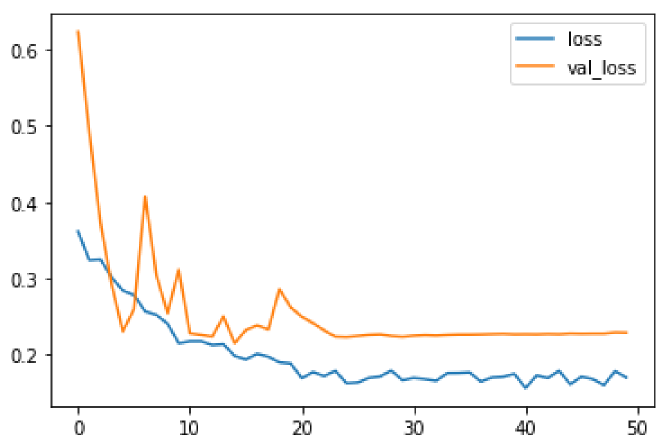

Fig. 4. Loss vs Epoch

When compared to InceptionV3, InceptionResNetV2, and ResNet-50 as the backbone, we discovered that ResNet-50 produces better results. Table 1 shows the comparison of the pre-trained models on various performance parameters.

Fig.7 shows some of the predictions made by the ResNet-50 model on the test data-set.

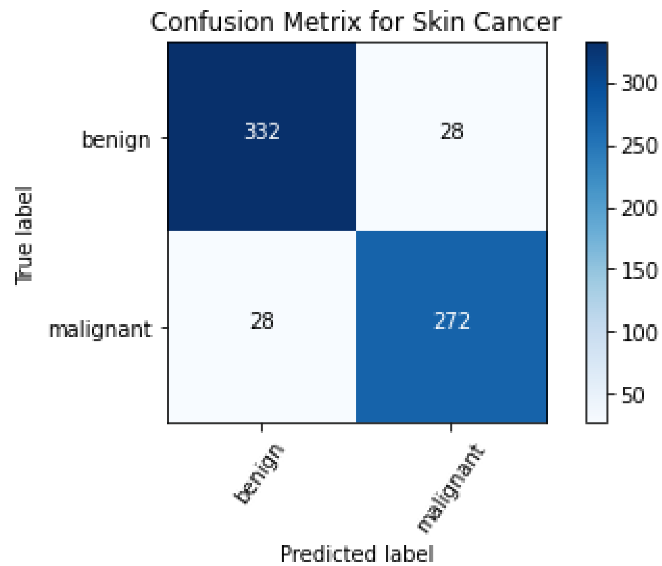

Fig. 5. Confusion Matrix

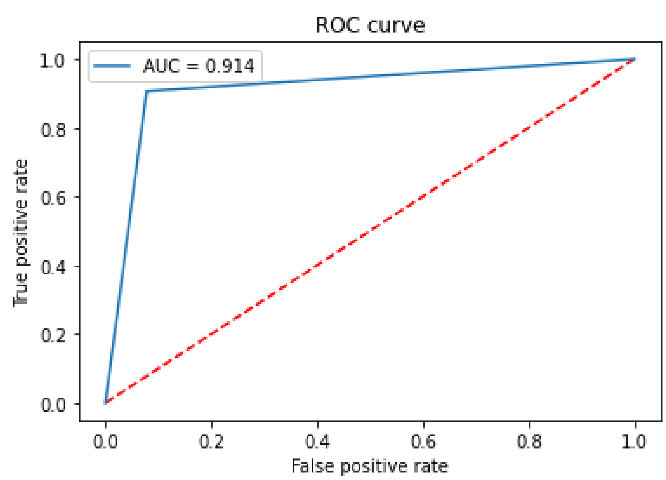

Fig. 6. ROC-AUC Curve

TABLE I
Comparison of Pre-Trained Models

Pre-Trained Models	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Inception-v3	0.891	0.92	0.71	0.80	0.838
ResNet-50	0.920	0.91	0.91	0.91	0.914
InceptionResNet-v2	0.907	0.90	0.70	0.79	0.839

V. Conclusion

This study looked at the potential of deep convolution neural networks to differentiate between benign and malignant skin cancer. We demonstrated that by employing extremely deep convolutional neural networks and fine-tuning them on dermoscopic pictures, we can obtain better diagnostic accuracy than physicians and clinicians. Given that the model performs at 92.04% accuracy for just 50 epochs, it is quite effective. Even

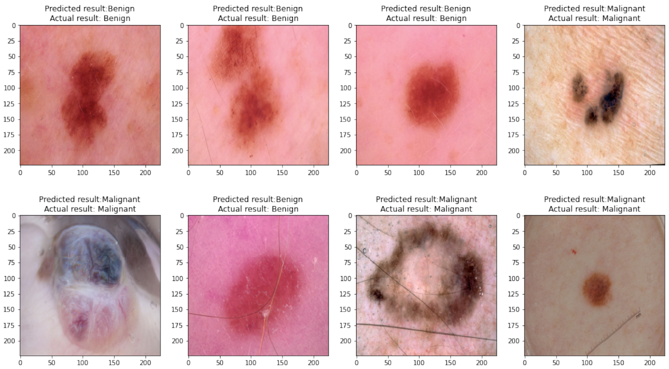

Fig. 7. Predictions made on the test data-set

better performance may be attained if the model is trained over a longer period of time. This model may be considered as a benchmark for skin cancer identification by supporting healthcare practitioners, according to the experimental and evaluation portion.

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