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A Survey on Skin Cancer Detection using Deep Neural Networks

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Abstract: Melanoma malignant growth is a kind of skin disease and is the most hazardous one since it causes the most skin malignant growth deaths [1]. Skin diseases is the most widely recognized human threat, is principally analyzed outwardly, [2, 3] starting with an underlying clinical screening and pursued possibly by dermoscopic investigation and a biopsy. Melanoma originates from melanocyte cells and are mostly dark colored or dark hued. However, the accurate recognition of melanoma is extremely challenging due to the following reasons: low contrast between lesions and skin, visual similarity between melanoma and non-melanoma lesions, etc. Deep convolutional neural networks show potential for better classification of cancer lesions. This paper presents various existing CNN based pretrained models for detection of melanoma skin lesions such as Google Inception V4, VGG16 and ResNet101 and test for the exploiting the features provided by these models to train the dataset and check for accuracy.
Keywords: Skin cancer; Melanoma; Malignant; Convolutional Neural Network

I. INTRODUCTION

In the previous 10-year time span, from 2008 to 2018, the yearly number of melanoma cases has expanded by 53%, somewhat because of expanded UV introduction [4]. In spite of the fact that melanoma is a standout amongst the deadliest kinds of skin disease, a quick determination can prompt an extremely high shot of survival. The first step in the diagnosis of a malignant lesion by a dermatologist is visual examination of the suspicious skin area. A correct diagnosis is critical because of the similarities of some lesion types; besides, the diagnostic precision relates firmly with the expert experience of the doctor.

People have been putting efforts to solve this problem using machine learning in past few years. This can help physicians as well as non-experts by saving time by automating the first step of diagnosis. Earlier researches mostly use the classical workflow of machine learning: preprocessing, segmentation, feature extraction, and classification. Nonetheless, an abnormal state of use explicit mastery is required, especially for feature extraction, and the choice of satisfactory feature is very tedious. In addition, errors and the loss of information in the first processing steps have a very strong influence on the classification quality. For example, a poor segmentation result often leads to poor results in feature extraction and, consequently, low classification accuracy. Artificial intelligent and deep learning procedure, fueled by cutting edge calculation capacity and expansive datasets individuals have gathered and distributed as open sources, have been overwhelmed in numerous zones and been demonstrated to surpass human execution in vital amusements like Go3, picture acknowledgment like ImageNet, language interpretation and speech recognition.

II. THEORY AND RELATED WORK

A. *Melanoma Cancer*

Melanoma originates from melanocyte cells, melanin creating cells that are typically present in the skin. Since most melanoma cells still produce melanin, melanoma is regularly darker or dark. Fig. 1 demonstrates the type of melanoma skin disease.

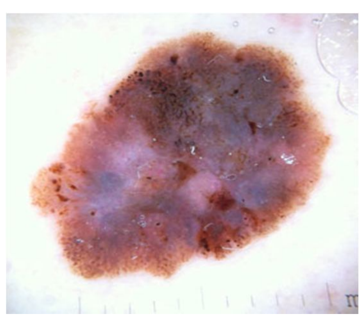

Fig. 1 Dermoscopy images of melanoma lesion

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Melanoma can show up on typical skin or can show up as a mole or other region of the skin that experiences changes. A few moles that emerge during childbirth can form into melanoma. Furthermore, melanoma can likewise happen in the eyes, ears, gingival of the upper jaw, tongue, and lips. Melanoma disease is regularly portrayed by the presence of new moles or when there is an adjustment fit as a fiddle from an old mole. Typical moles more often than not have one shading, round or oval, and are under 6 mms in measurement [5], while melanoma has these attributes:

1) Has more than one shading. Melanoma is normally a blend of a few hues.
2) Has an unpredictable shape. Melanoma has a sporadic shape and can't be isolated down the middle.
3) Its width is more prominent than 6 mm
4) Enlargement or development: moles that change shape and size inevitably will generally progress toward becoming Melanoma.

B. Deep Learning

Deep learning is an AI method that uses numerous layers of nonlinear data processing to perform feature extraction, pattern recognition, and characterization [6]. Deep Learning uses neural networks to actualize issues with substantial datasets. Deep Learning procedures give an extremely solid design to Supervised Learning. By including more layers, the learning model can more readily represent marked picture information. In Deep learning, a model figures out how to characterize from pictures, content, or sound. Similarly, as a PC is prepared to utilize substantial quantities of information collections and after that change the pixel estimation of a picture to an inside portrayal or vector highlight where classifiers can recognize or group designs in the information [7].

C. CNN

Convolutional Neural Network (CNN) is one of the deep learning's algorithms that is professed to be the best model for taking care of issues in object categorization or recognition. CNN is the advancement of Multilayer Perceptron (MLP) which is intended to process two-dimensional information. CNN is incorporated into the sort of Deep Neural Network on account of the high network density and many applied to image information. On account of image classification in research on virtual cortex on feline's visual sense, MLP is less reasonable for use since it doesn't store spatial data from image information and believes every pixel to be a free feature that results in troublesome outcomes. CNN was first created by Kunihiki Fukushima under the name NeoCognitron. This idea was later created by Yann LeChun for numerical acknowledgment and penmanship. In 2012, Alex Krizhevsky effectively won the 2012 ImageNet large Scale Visual Recognition Challenge with his CNN application. This is the snapshot of verification that the Deep Learning strategy with CNN technique has ended up being fruitful in conquering other Machine Learning strategies, for example, SVM on account of item characterization in pictures [8].

D. Related Work

The research has related to works by- first, Andre Esteva et.al. 2017 [9], for example ―level order of skin disease with profound neural systems; and second, T.J. Binker et al. 2018 [10], for example ―Skin Cancer Classification Using Convolutional Neural Networks: Systematic Review. The two investigates are about general skin malignant growth, yet our examination is increasingly explicit for melanoma skin disease.

III. METHODOLOGY

A. Datasets

Our dataset comes from the ISIC Archive. The ISIC Archive information utilized is made carefully out of melanocytic lesions that are biopsy-demonstrated and commented on as benign or malignant. In our test sets, melanocytic sores incorporate melanomas malignant—the deadliest skin malignancy—and benign nevus.

B. Data Preparation

Blurred pictures and far-away pictures were expelled from the test and validation sets, however, were yet utilized in preparing. Our dataset contains sets of pictures relating to a similar sore(lesion) yet from various perspectives, or different pictures of comparable lesions on a similar individual. While this is valuable training data, broad consideration was taken to guarantee that these sets were not part between the preparation and validation sets. No overlap (that is, same injury, various perspectives) exists between the test sets and the preparation/approval information.

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Thus, a split is done in a way that 80 percent of the data is used for training and 20 percent is used for validation. However, the split is done in a stratified way, with the goal that each split has a considerable measure of each class. At long last, these cuts of the dataset are kept isolated and are utilized in that capacity for the trial.

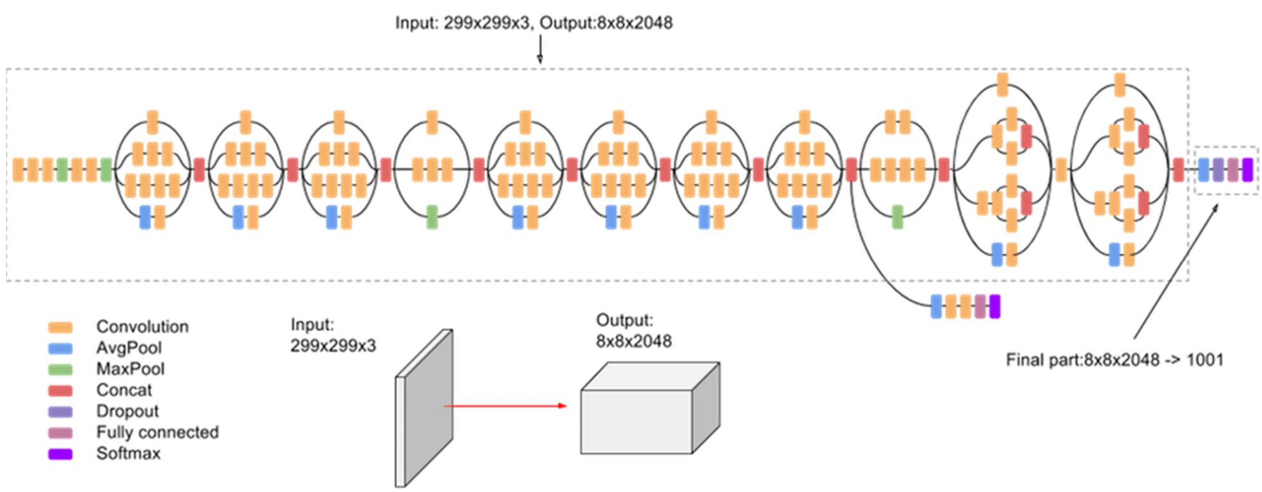
C. Data Augmentation

Data Augmentation is a method utilized where we don't have an infinite amount of information to train our models. This should be possible by acquainting arbitrary changes within the information. In image classification, this can be done as pivoting, flipping and cropping the picture. These permutations add greater variations to the input, consequently, this could mean an over fitting reduce in our model by showing it invariances in the information domain [11,12].

Consequently, these changes don't change the significance of the input, accordingly, the label initially credited to it holds its significance. A few transforms in the image should be a possible skeptic to the field of use (for example translation), some different changes are qualified for area specific attributes. For this work we utilized an extra change that randomizes the characteristic light impact in the image, this was done to imitate the changes seen in inside clinics because of various light sources. Moreover, to expand the changeability included by enlarging information, the likelihood of use and extent inconstancy are added to the changes.

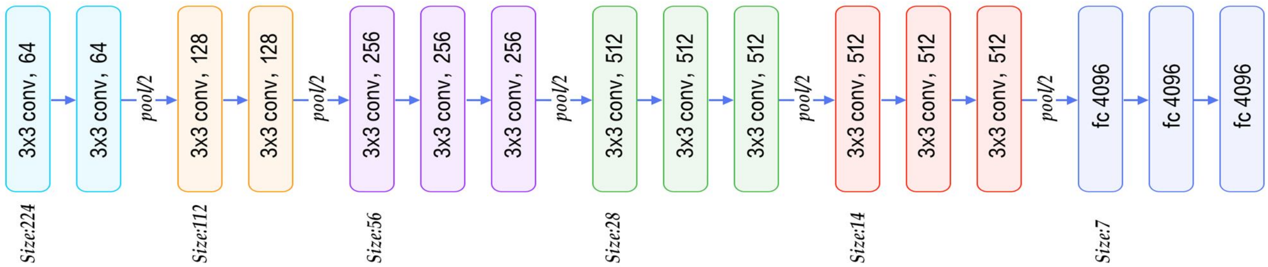
D. Google's Inception v3

We use Google's Inception v3 CNN architecture pretrained to 93.33% top-five accuracy on the 1,000 object classes (1.28 million images) of the 2014 ImageNet Challenge. We then remove the final classification layer from the network and retrain it with our dataset, fine-tuning the parameters across all layers. During training we resize each image to 299 × 299 pixels in order to make it compatible with the original dimensions of the Inception v3 network architecture and leverage the natural-image features learned by the ImageNet pretrained network. This procedure, known as transfer learning, is optimal given the amount of data available. Our CNN is prepared utilizing backpropagation. All layers of the network are tweaked utilizing the same global learning rate of 0.001 and a decay factor of 16 each 30 epochs.



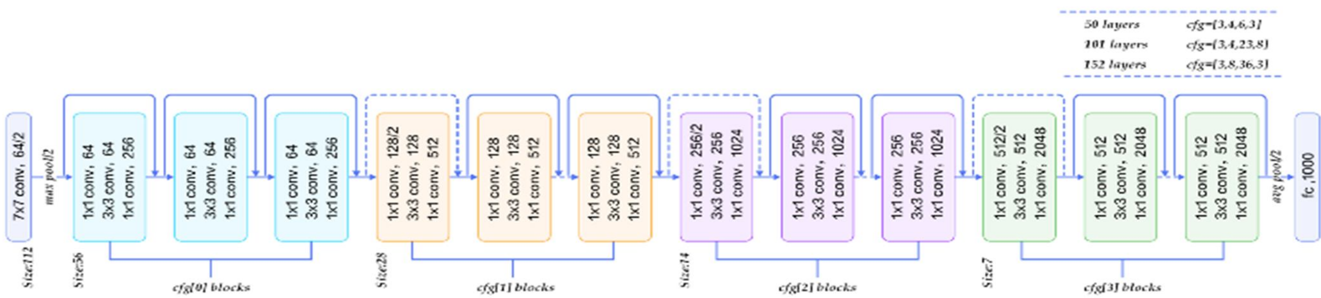
E. VGGNet

VGGNet is invented by VGG (Visual Geometry Group) from University of Oxford, Though VGGNet is the 1st runner-up, not the winner of the ILSVRC (ImageNet Large Scale Visual Recognition Competition) 2014 in the classification task, which has significantly improvement over ZFNet (The winner in 2013) [13] and AlexNet (The winner in 2012) [14]. Again, in VGGNet we remove few the final classification layers and retrain it with our dataset to classify images into benign or malignant. VGGNet consists of 16 convolutional layers and is very appealing because of its very uniform architecture.



F. ResNet

The purported Residual Neural Network (ResNet) by Kaiming He et al presented anovel design with "skip associations" and features heavy batch normalization. Such skip associations are otherwise called gated units or gated recurrent units and have a solid likeness to later effective components connected in RNNs. On account of this system they had the capacity to prepare a NN with 152 layers while as yet having lower intricacy than VGGNet.



G. Transfer Learning

Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task. It is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks given the vast compute and time resources required to develop neural network models on these problems and from the huge jumps in skill that they provide on related problems. In our trial we have used three pre-trained models (Google's Inception, VGGNet and ResNet), where we apply transfer learning to use the pre-trained weights and retrain those models after removing their classification layers for classifying benign vs malignant. Transfer learning is an optimization, a shortcut to saving time or getting better performance.

H. Performance Metrics For The Classifiers Used

A classifier classifies out each article to a class. This task is commonly not perfect, and articles might be assigned to the wrong class. To assess a classifier, the genuine class of the articles must be known. To assess the classification quality, the class assigned out by the classifier is compared with the real class. This enables the items to be partitioned into the accompanying four subsets:

1) True positive (TP): the classifier correctly predicts the positive class.
2) True negative (TN): the classifier correctly predicts the negative class.
3) False positive (FP): the classifier incorrectly predicts the positive class.
4) False negative (FN): the classifier incorrectly predicts the negative class.

In view of the cardinality of these subsets, measurable amounts for the classifier would now be able to be determined. A typical and generally utilized amount is accuracy, which is just a sensible measure if the distinctive classes in the dataset are roughly similarly dispersed. Accuracy is calculated by (TP + TN)/ (TP + TN + FP + FN). It specifies the percentage of objects that have been correctly classified.

Two other critical measurements are sensitivity and specificity, which can be connected regardless of whether the diverse classes are not similarly circulated. Sensitivity indicates the ratio of objects correctly classified as positive out of the total number of positive objects contained in the dataset and is calculated by TP/ (TP + FN). Specificity indicates the ratio of negative objects correctly classified as negative out of the total number of negative objects contained in the available dataset and is calculated by TN/ (TN + FP).

IV. PRINCIPAL FINDINGS

One issue with the examination of skin lesion classification techniques is that the considered formulations of the individual works differ, at times just marginally. This not only occurs for the considered training classes and the used data, but also for presented statistical quantities. Moreover, some works use non-public archives of skin clinics in addition to publicly accessible data archives [15, 16]. This makes it even more difficult to reproduce the findings. Since 2016, the ISIC Melanoma Project has attempted to improve this aspect by establishing a publicly accessible archive of dermoscopic skin lesion images as a benchmark for research and education [17]. In addition, they announced a yearly challenge in which clearly defined problem must be addressed. It would be desirable if more work would compare itself with this benchmark to achieve a better ranking of the techniques in this state of experimentation.

Another important issue in this research field is the development of large public picture archives with pictures as representative of the world population [18]. The existing image archives mainly contain skin lesions from light-skinned people or white peoples as the issue is more prominent in these people. The images in the ISIC archive, for example, come mainly from the USA, Europe, and Australia. To achieve an accurate classification for dark-skinned people as well, the CNN must learn to abstract from the skin color. However, this can only occur if it observes enough pictures of dark-skinned people during the training, so dataset is still incomplete in this aspect.

V. CONCLUSION

CNNs show an elite as best in class skin lesion classifiers. Sadly, it is hard to look at changed characterization strategies since certain methodologies utilize non-public datasets for training and additionally testing, subsequently making reproducibility troublesome. Future productions should utilize freely accessible benchmarks and completely uncover strategies utilized for training to permit comparability.

In this paper, we examined the significance of programmed characterization strategy to help skin lesions classification. Moreover, we recorded a gathering of researches and their accomplished results for the same issue. In any case, it is yet an issue with a few troubles, significantly more when we consider clinical pictures, that may exhibit an enormous assorted diversity because of factors for example, cameras and conditions.

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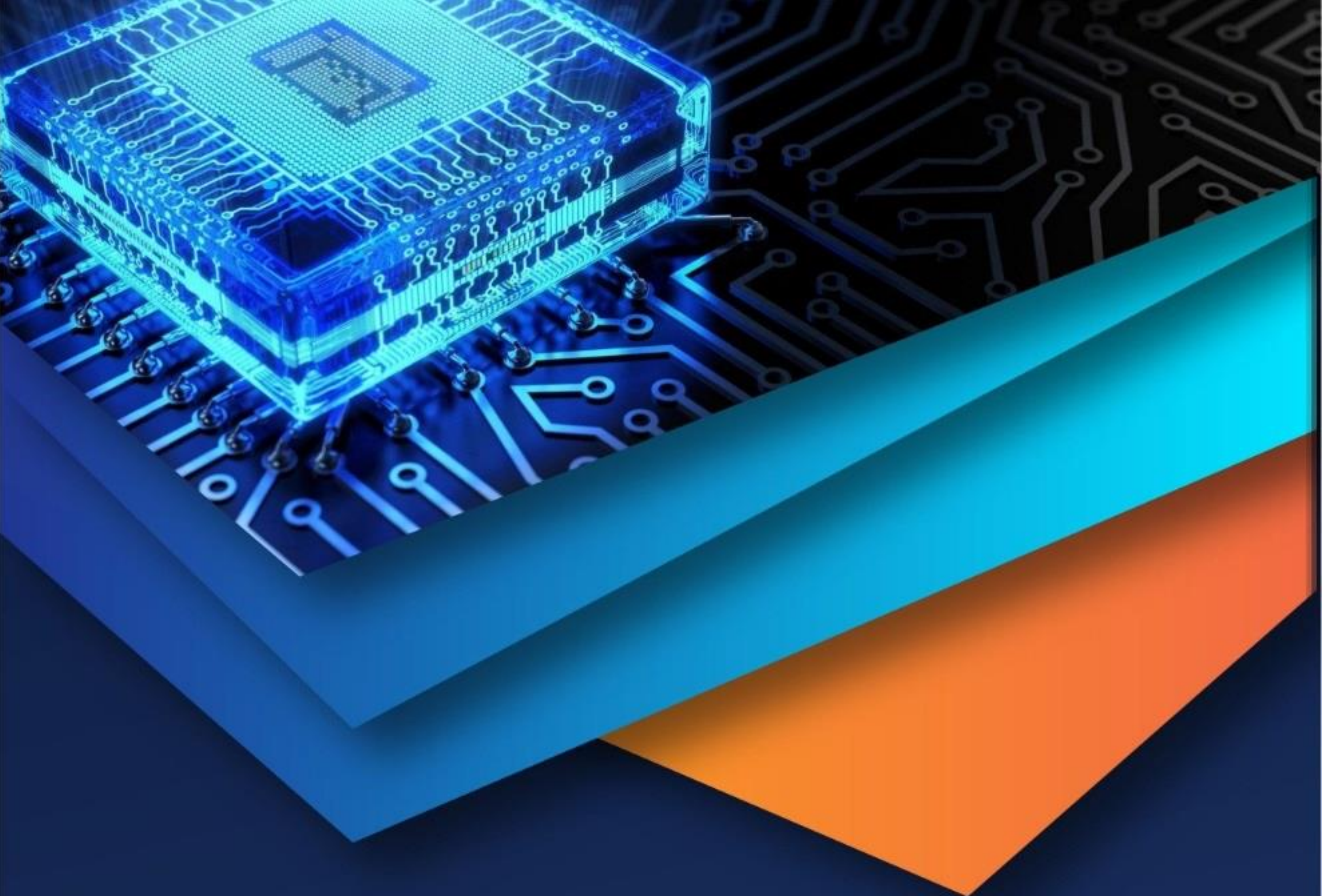

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