Dermoscopic classification using Image processing and CNN

Tejas Ravi Ghatikar
UG Scholar, Dept. of Information Science, B.M.S. College of Engineering(affiliated to VTU), Bengaluru, India

Abstract—Melanoma is one of the deadliest forms of skin cancer accounting to more than 70 percent of skin cancer deaths despite it being the least common skin cancer. In the early stages, melanoma can be treated successfully with surgery alone and survival rates are high, but after metastasis survival rates drop significantly as it is known to spreads to other parts of the body. Hence to combat this, Early detection of melanoma is imperative. I propose an automated melanoma detection model by analysis of skin lesion images using SE-ResNeXt a variant of ResNet that uses squeeze-and-excitation blocs to bring significant improvement in performance of existing CNNs. I performed the evaluation using a large publicly available dataset ISIC 2020 Challenge Dataset, generated by the International Skin Imaging Collaboration containing skin lesion images from several primary medical sources, have successfully demonstrated classification performance with an accuracy achieved about 90%.

Keywords— melanoma, convolutional neural network, image processing, SE-ResNet

I. INTRODUCTION

Skin diseases are among those groups of diseases whose prevalence has been steadily rising over time. Only in India, about 200 million people suffer from one or the other forms of skin diseases. People often neglect skin diseases and fail to seek appropriate and necessary treatment. This is particularly evident in rural and economically backward areas to many factors such as lack of awareness, poverty, lack of resources, etc , This is even higher when it comes to the case of Melanoma skin cancer.

In India, the incidence of melanoma of the skin in the North region is 1.62 for males and 1.21 for females for every 1,00,000 people [1] while invasive melanoma accounts for about 1% of all skin cancer cases but still is the vast majority of skin cancer deaths. In 2021, an estimated 106,110 new cases of invasive melanoma and 101,280 cases of in situ melanoma will be diagnosed in the US with around 7,180 people to die from the deadly disease [2]. It can be challenging for doctors to precisely identify the sort of skin disorders that a patient is suffering from when they are approached by a patient furthermore difficult to exactly detect the type of skin diseases the patient is getting affected with. Especially when it comes to the diseases like Melanoma, it is quite challenging to differentiate between diseases without performing any tests. In men, it is frequently to be situated on the skin, on the head, on the neck, or the area between the shoulders and the hips. While it often appears on the skin, on the lower legs or area between the shoulders and the hip for women [3].

This disease causes scarring and disfigurement of the skin, as well as severe pain and bleeding. Due to an increase in pollution activities in the environment, the ozone layer is getting depleted day by day, allowing ultraviolet (UV) radiation to reach the earth's surface directly. This direct exposure to UV radiation is mainly responsible for skin cancer [4] . The number of skin cancer cases occurring every year is found to be exceeding the number of total cases of all other types of cancer occurring globally. Early detection of skin cancer in a patient improves his chances of recovery and saves his life by providing proper treatment and care.

Visual examinations and manual techniques are typically used to detect skin cancer, but these procedures take longer and are more likely to result in errors, resulting in low accuracy [5] . Without additional technical support, dermatologists have a 65% to 80% accuracy rate in melanoma diagnosis [6] furthermore the combination of visual inspection and dermatoscopic images ultimately results in an absolute melanoma detection accuracy of 75% to 84% by dermatologists and with computer-based models based on feature extraction and machine learning are being developed, but they have proven to be inefficient.

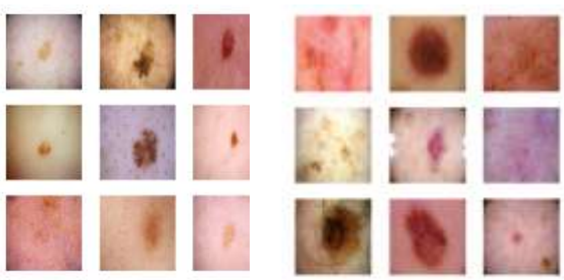
In today's world, deep learning is becoming more popular, In deep learning, the convolution neural networks (CNN) algorithm is efficient in feature extraction and classification. CNNs are neural networks with a specific architecture that have been shown to be very powerful in areas such as image recognition and classification [7]. In consideration of high and effective performance of the CNNs , they are used in a lot of applications in different parts of medical imaging techniques which includes lesion classification, MR images fusion, breast cancer and tumor diagnosis, and panoptic analysis.

Characterization of melanoma disease was carried out earlier. Support Vector Machine (SVM), k-Nearest Neighbor (KNN), decision tree techniques were used to detect these deadly diseases with a precision of 0.8-0.9 and again, CNN and ResNet was used which could get a precision of 0.91. In 2012, the classification of skin disease started and over 2017, ResNet was introduced to get a better accuracy and hence speed up the process of easy identification of these diseases. Over the years these classification methods are improving, and the accuracy results are getting better. New techniques in deep learning is helping medical industry in a big way [8].

It takes highly specialized practitioners to properly recognize the extent of the skin disease and its spread. Sometimes, the images are with noise and other difficulties like variations in skin tone, low contrast and these images should be segmented to remove noise, and image artefacts such as hairs and bubbles around the image. Since the presence of hair in dermoscopic images might conceal important information about the depicted skin lesions, several methods have been developed with Lls algorithm proven to be the most effective for the removal of light brown hair [9]. Thus filtering of images are important to get accurate results.

Utilizing CNNs which must be pre-prepared with a large set of data of characteristic images, as upgraded includes image filters that can potentially overcome the drawbacks of conventional methodologies. Several works have attempted to extract profound highlights from skin sore pictures and then train an old-style classifier. There is a very limited amount of data publicly available for the classification of skin lesions. Almost all published methods use datasets that contain far less than 1000 training data points per training class. In comparison, well-known CNN models for image classification, such as AlexNet, VGG GoogLeNet, or ResNet, are trained via the large image database ImageNet and have over 1000 training images for each training class [10].

Unlike previous works In this paper, I will explore the ResNet mechanism and assess all possible combinations of highly advanced image augmentation pipelines for deep CNN models (seResNext50 32X4d) for accurately classifying skin diseases and producing a report in a user-friendly format for detailed analysis and identification of skin diseases.



Benign *Malign*

II. LITERATURE SURVEY

The skin cancer rate is increasing at an alarming rate because of pollution and climatic changes occurring in our environment. This skin cancer is basically of two major types melanoma and non-melanoma. The vast majority of melanomas are caused by the sun with one of the studies in UK found that about 86 percent of melanomas can be attributed to exposure to ultraviolet (UV) radiation from the sun and about 90 percent of nonmelanoma skin cancers are also associated with exposure to ultraviolet (UV) radiation from the sun [11]. While UV exposure and sunburns, particularly during childhood, are risk factors for the disease. Not all melanomas are exclusively sun-related, other possible influences include genetic factors and immune system deficiencies. Genetic factors such as atypical moles inherited which tend to be irregular shape or colour and may be larger than usual which results in a condition called familial atypical multiple mole melanoma syndrome (FAMMM) which increases your risk of getting melanoma. Scientists think that around 10 out of 100 cases of melanoma (10%) might be linked to inherited faulty genes. A gene called CDKN2A is known to cause FAMMM [12]. The incidence of melanoma among children, adolescents, and young adults has reached epidemic proportions, increasing more than 250% over the past 4 decades, with young females at highest risk for the deadly cancer, according to a study in US [13] but also observed that in both sexes, the incidence is rising, with a 4.4% increase in men and a 3.1% increase in women per year from 2012 to 2019. but, the rate of men and women below 50 years decreased by more than 1% every year [14].

III. EXISTING SYSTEM

Currently, In the clinical process, skin biopsies are performed in which infected tissue is removed from the body under anaesthesia, so there are risks involved such as bleeding, hygienic process, and pain caused while removing the skin tissue, moreover Skin biopsy equipment had low availability at health facilities sampled across 7 LICs, with decreased availability at lower-level health facilities and in the public sector. Fewer facilities offered minor surgical procedures free of cost, further limiting biopsy access, and also seen that availability of biopsy equipment was not assessed [15]. In India cost of skin biopsies range from 600 Rs to 4000 Rs which is quite a hefty amount in villages. while it also found that the relationship between skin biopsy and melanoma incidence rate can sometimes result in overdiagnosis which is a result of increased detection of otherwise biologically benign lesions that portend no additional mortality risk [16].

Other methods include using technical ways to find skin cancer with mobile apps developed such as ‘UMSkinCheck’ which guides you step-by-step for a full body skin cancer self-exam, as well as creating and tracking the history of moles, growths, and lesions and 'Skin vision' which uses deep learning to analyse photos of the skin and aid in the early detection of skin cancer but research over apps were found to incorrectly categorize a large number of skin lesions, with one missing nearly 30% of melanomas, classifying them as low-risk lesions [17].

Many computer-based diagnosing models have been developed to diagnose skin cancer that relies on feature extraction and classification, for example, ABCD rules i.e (asymmetry, border, color, diameter, and evolving**)** scoring pattern used to quantify dermoscopy findings. When using the implementation of the ABCD rule in one study, they reported a sensitivity and specificity of 92.8 and 90.3% respectively. However, even with achieving high accuracy, the approach misclassified 12 lesions: seven melanomas and five benign cases [18]. Observing other methodologies such as the seven-point checklist, and using well-developed classifiers like SVM but these are limited to dermoscopy or histopathology images data [5]. These procedures will not give good performance in every case and their efficiency is also low.

IV. RESEARCH METHODOLOGY

A. Dataset

The dataset used is International Skin Imaging Collaboration
(ISIC) for skin lesion analysis towards melanoma detection with the classification of testing images into two classes which are malignant and benign, the data contains attributes such as image name, patient id, sex, age approximate, diagnosis, benign/malignant, target, etc. which is split into training and testing with train data consisting of 33126 images and test data with 10982 images. The images provided are in JPEG and TFRecord format. Images in TFRecord format have been resized to a uniform 1024x1024.

B. Pre-processing

As the dataset is observed to be having more benign data dataset hence it is possible that the split may not accurately reflect the proportion of class labels between train and test data in the actual dataset and thus a bias will be based on benign class which will impact the performance of the classifier significantly.

In order to overcome the bias, we use k-fold cross-validation to ensure that the class labels have the same distribution in each fold. This cross-validation ensures that we are able to make predictions using k different models on all of the data. Early stopping and learning rate scheduler also used for training the model faster.

I have also used Binary Cross Entropy (BCE) loss for the problem since classification of the images into classes: benign or malignant is required. The formula of the BCE loss is as given below:

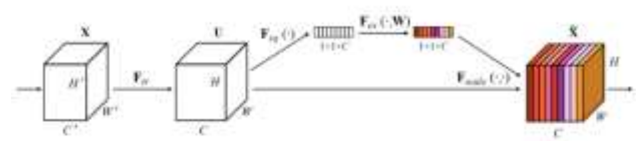
$$L = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log(p_i) + (1-y_i)\log(1-p_i)\right)$$

Where ***pi*** is the predicted probability of the image being malign for the *ith* sample, and *yi* is the classes (0 as benign and 1 for malign).

C. Deep Learning Models

Traditional convolutional neural networks (CNNs) use convolution operations to fuse information both spatially and channel-wise, but in the 2017 ImageNet challenge, Jie Hu et al. proposed a novel architecture Squeeze and Excitation Networks (SENets) that focuses on the channel-wise information correlation. This network outperformed the results from the previous year by 25%.

The basic idea behind this approach was to adjust the feature map channel-wise by adding the parameters to each channel of a convolutional block. These parameters, like attention in recurrent neural networks, represent the relevance of each feature map to the information (RNNs) [19].



The Squeeze-and-Excitation (SE) block is depicted above, where it performs a series of operations: squeeze and excitation, allowing the network to recalibrate the channel-wise information, i.e. emphasize informative feature maps and suppress less useful feature maps. By aggregating feature maps across spatial dimensions and using global average pooling, the squeeze operation generates a channel descriptor that expresses the entire image. The excitation operation generates channel-wise relevance by employing two fully connected

(FC) layers, each of which captures channel-wise dependencies. This block can be directly applied to existing architectures such as ResNet, as shown in the Figure below.

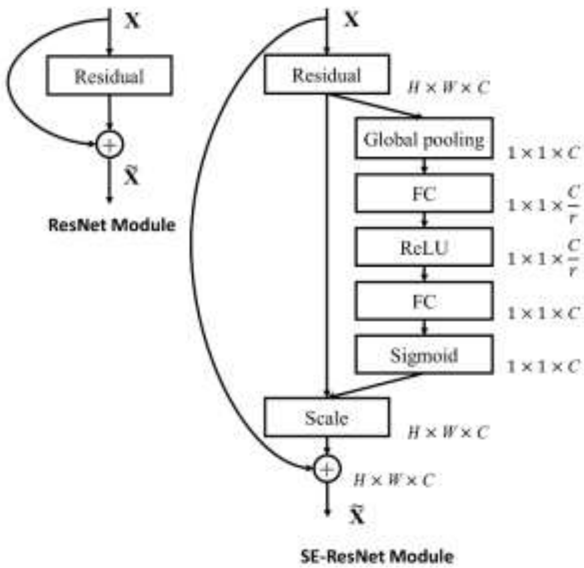


Figure 2. Schema of SE-Inception and SE-ResNet modules where residual module is on the left and SE-ResNet module right.

The computational overhead of the network is determined by where the SE block is used. The computational overhead increased slightly, which is understandable given the network's performance boost. The authors used the SE block at earlier layers to reduce computation overhead because the number of parameters increases as the feature maps increase channel-wise at later layers.

D. Evaluation

The area under the ROC curve (AUC) was used as an evaluation metric for the problem due to an imbalanced dataset. A ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classifier at various classification thresholds. It is a measure of how well the model is capable of distinguishing between the different classes. This curve plots two parameters mainly TPR and FPR. Intuitively, AUC-ROC score of 0.0 means a model predicts extremely terrible, while AUCROC of 1.0 indicates a model predicts 100% correct

In this section, I compare my proposed approach to previous approaches using the ISIC 2020 Challenge Dataset, which is part of the larger ISIC Archive, which contains the largest publicly available collection of quality-controlled dermoscopic images of skin lesions generated by the International Skin Imaging Collaboration (ISIC). Some medical research institutes collect all images with corresponding diagnosis information labels. Because of the distribution imbalance, I used K-folds cross-validation with a batch size of 32 and augmentation to improve the quality of trained models. After 17 epochs, the final trained model is generated. I plot the AUC-ROC score curve in the training phase using the settings described above, as shown in Figure

3.

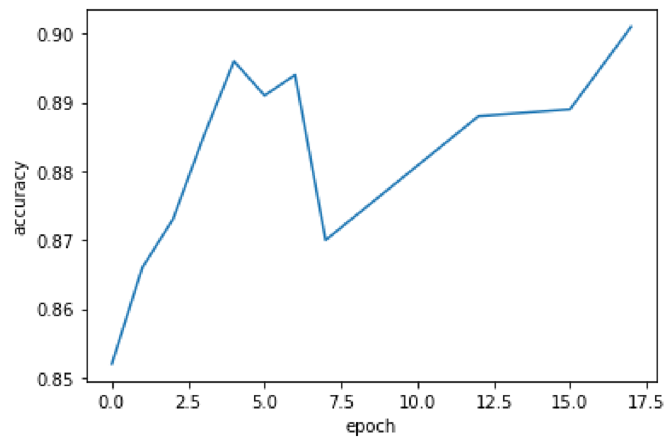


Figure 3. Indicates model accuracy when training dataset

Because different model evaluation settings require different settings, it is necessary to compare previous models and my proposed model in the same experimental environment. To do so, I recreate the VGG16 and VGG19 melanoma detection models. Then train and test them on the same ISIC 2020 Challenge Dataset. It can be observed from Table 1 that my proposed model has achieved better classification performance compared to other recent methods. Numerically, my model obtains state-of-the-art AUC-ROC score of 0.901, which is 1.2% higher than the counterpart of VGG16, also 0.9% higher than VGG19. Therefore, the experimental results demonstrate the effectiveness of my model architecture.

Table 1. Indicates model based on SEResNeXt50_32x4d performance results on ISIC 2020 Challenge Data. All models trained and tested on this dataset

model	AUC-ROC SCORE
VGG16	0.889
VGG19	0.892
SEResNeXt50_32x4d	0.901

I also tested the BCE loss for the mentioned models and found to have a lesser BCE loss compared to VGG models.

Table 2. Indicates model based on SEResNeXt50_32x4d performance results on ISIC 2020 Challenge Data based on BCE loss results.

Model	BCE Loss
SEResNeXt50_32x4d	0.886
VGG19	0.899
VGG16	0.901

V. CONCLUSION

Automated melanoma recognition in dermoscopy images is a very challenging task due to the low contrast of skin lesions, the large intraclass variation of melanomas, the high degree of visual similarity between melanoma and non-melanoma lesions, and the existence of many artifacts in the image. In this paper I methodically study melanoma detection and understand through my observations, that SE model seResNext50 is capable of capturing more complex features from clinical images of skin lesions and assisting practitioners in identifying the spread of the disease at an early stage, allowing the population to eradicate this type of disease. CNNs prove to be very useful in helping the doctors for this disease. However the other trained models like Efficient-B6, ResNet-34 are very helpful in achieving better results of classification. Efficiency can be improved by increasing the number of epochs and the number of transitions per each epoch while another improvement can be made by adding extra layers or neurons to the seResNext50 output to increase complexity and analyse overfit/underfit ratios.

The detection of melanoma skin cancer can be automated, saving doctors time and allowing for more accurate diagnosis. As a result, integration of this model into a web-based or mobile application is required in the future to overcome the challenge of visiting hospitals with resources to test and detect melanoma, as well as to facilitate and reduce the cost of melanoma diagnosis.

VI. REFRENCES

[1] “Labani, S., Asthana, S., Rathore, K., & Sardana, K. (2021). Incidence of melanoma and nonmelanoma skin cancers in Indian and the global regions. Journal of Cancer Research and Therapeutics, 17(4), 906.”.

[2] https://impactmelanoma.org/american-cancer-society-releases-2021-cancer-facts-figures-report/.

[3] Zito, Patrick M., and Richard Scharf. "Melanoma of the head and neck." In *StatPearls [Internet]*. StatPearls Publishing, 2021

[4] Sanketh, Ravva Sai, et al. "Melanoma disease detection using convolutional neural networks." 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 2020.

[5] Zhang, Long, Hong Jie Gao, Jianhua Zhang, and Benjamin Badami."Optimization of the Convolutional Neural Networks for Automatic Detection of Skin Cancer." Open Medicine15, no. 1 (2020): 27-37.

[6] Argenziano G, Soyer HP. Dermoscopy of pigmented skin lesions: A valuable tool for early diagnosis of melanoma. Lancet Oncol. 2001 Jul;2(7):443–449.

[7] N. Tajbakhsh, J.Y. Shin, S.R. Gurudu, R.T. Hurst, C.B. Kendall, M.B. Gotway, J. Liang, Convolutional neural networks for medical image analysis: Full training or fine tuning? IEEE Trans. Med. Imaging 35 (5) (2016) 1299–1312.

[8] Gouda, Niharika, and J. Amudha. "Skin cancer classification using resnet." 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA). IEEE, 2020.

[9] Maglogiannis, Ilias, and Kostantinos Delibasis. "Hair removal on dermoscopy images." 2015 37th
Annual International Conference of the

IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2015.

[10] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems* 25 (2012).

[11] Skin Cancer Facts & Statistics , Skincancer.org

[12] Risks and causes of melanoma, Cancerresearchuk.org

[13] Why Melanoma Rates Are Increasing in Adolescents and Young Adults, Especially Among Females , Demytra Mitsis, MD, and Nikhil I. Khushalani, MD

[14] Skin cancer statistics , wcrf.org

[15] McMahon, Devon E., et al. "Skin Biopsy Equipment Availability Across 7 Low-Income Countries: A Cross-Sectional Study of 6053 Health Facilities." *JAMA dermatology* 157.4 (2021): 462-464.

[16] Weinstock, M. A., et al. "Skin biopsy utilization and melanoma incidence among Medicare beneficiaries." *British Journal of Dermatology* 176.4 (2017): 949-954.

[17] 4 ways to check for skin cancer with your smartphone, Amanda Capritto

[18] Kasmi, Reda, and Karim Mokrani. "Classification of malignant melanoma and benign skin lesions: implementation of automatic ABCD rule." IET Image Processing 10.6 (2016): 448-455

[19] Hu, Jie, Li Shen, and Gang Sun. "Squeeze-and-excitation networks." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.