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AN IMPLEMENTATION OF HYBRID CONVOLUTION NEURAL NETWORKS FOR SKIN CANCER CLASSIFICATION

G Hemalatha Research Scholar PG & Research Department of Computer Science, Presidency College
Dr.S. Mary Vennila Research Supervisor PG & Research Department of Computer Science, Presidency College

ABSTRACT

Skin cancer is a most common, abnormal development of skin cells in humans. It can occur both when the skin is exposed to the sun and when it is not. Skin conditions are worsened by exposure to pollutants, chemicals, and cosmetics. The medical field is being improved by innovating very new technologies. Early diagnosis plays an important role in identifying and curing disease, but even the most experienced physicians have been harder to identify and classify the early stage of skin disorders. Therefore, computational skin cancer detection is essential for early detection of the disease. This approach can reduce mortality in cancer patients. The proposed architecture focuses on an automated system for predicting dermatological diseases. The model uses preprocessed images and analyzed four types of pretrained models Inception V3, ResNet 152, Mobile Net V2, and Xception Network with base Convolutional Neural Network model. Four new models were generated. The best performing model was selected based on accuracy. Finally, two hybrid models were created by combining Inception V3, ResNet 152 and MobileNet V2, Xception Network. Result of the first hybrid model (Inception V3 network and ResNet 152) gave 85.9% testing accuracy and the second hybrid model (MobileNet v2 and Xception network) showed 88.8% testing accuracy. The proposed model requires less human intervention in the cancer prediction process.

Keywords: Skin cancer detection, CNN, Inception V3, ResNet 152, MobileNet V2, Xception Network.

I.INTRODUCTION

A malignant tumor in skin which grows irregular and unconditional is called skin cancer. Maximum malignancies are created by exposed skin from UV (Ultra Violet) radiations [1]. Deeper layers of the skin safeguarded by the melanin from the sun are the reason for skin tone. When melanocytes grow abnormally and out of control creates melanoma. It can affect skin or travel through the blood and lymphatic system to expand the cancer cells to others organs and bones.

Melanoma damages the skins to an extent by damaging the pores. Early stage of detecting melanoma can be cured, but somewhat it is difficult to predict this at the initial stage, but most melanomas will eventually spread to other parts of the body if left untreated. Early detection to remove melanoma and surgery have successfully cured most cases of melanoma. However, in the later stages, it is rarely cured.

1% of the skin cancer is only caused by melanoma, the remaining 99% may be basal or squamous cell carcinomas [2]. In America, It is the most general type of cancer, a serious illness. Not less than 5 million cases are recorded every year by various skin diseases in the United States alone [3]. It increases gradually over the years [4]. Melanoma is one of the most dangerous skin cancers which leads to death [5]. In 2022, nearly 1 lakh of skin cancer cases were filled by the American Cancer Society, out of which men and women were 57% and 43% respectively [2].

Melanocytes (squamous cell layers) are seriously affected by melanoma. Depending on the skin cancer cell growth, it can be classified either Benign or Malignant. In the Benign stage the skin area looks like a mole or tag, which is mostly not considered as cancer whereas the patient who is in a later stage, Malignant require immediate medical care [6]. According to statistics, about 1,361,282 people had melanoma in 2019 [7]. There are 57,043 was died out of 3, 24,635 were found melanoma in the year 2020 [8]

II LITERATURE REVIEW

Dermatologists detect suspicious tumors with the help of dermatoscopy and biopsy [8]. As it takes a long time, the patient may move to the next stage. In the paper of [9], dermatoscope image performance and absolute accuracy were included. The precision of skin cancer detection associated with the experience and the skill of the physician [10]. Skin disease prediction takes a long time, the patient becomes hopeless and tiring [11]. Even in the absence of experts in the diagnosis process, the computer aided analysis help the physician. The wide variety of methods has been adopted for this purpose [12]. The image processing methods are used to extract the features for classification [13].

Fam etc. [14] used image enhancement techniques to extract ROI. Support Vector Machine classification algorithm used on the preprocessed images to the accuracy of 87.2%. A deep residual network model was proposed by Yu et al. [15] to extract ROI for classifying the images; it achieves an accuracy of 85.5%. Yu et al. [16] constructed a new model with deep CNN and FV coding techniques to get the required features. ISIC 2016 dataset used to train the model produces 86.54% accuracy. Binker et al. [17] uses ResNet50 which is a kind of pretrained model to predict cancer and this model attained the sensitivity of 77.9% and specificity of 82.3%. ResNet152 model used by Han et al. [18] to predict different types of skin lesions, this proposed model gains specificity of 87.63% and mean sensitivity is 88.2%.

Aldwgeri A. and Abubacker NF [19] examined numerous cases. The earlier CNN was trained from the ground with both balanced and unbalanced data from the HAM10000 dataset and the outcome were 64% and 57% with the respect to the accuracy of balanced and unbalanced data. Later variants of pretrained models VGG19, ResNet50, InceptionV3, DenseNet121, Xception, and VGG16 were used in the process of categorizing cancer.
The new variants were constructed the rescaled input image to 299*299 pixels with addition of softmax layer, pooling layer and a 0.5 dropout layer. The loss function optimizer used was categorical and Adam respectively. The selected stack size, number of epochs, learning rate were 32,60, and 0.0001 respectively. The accuracy gained by the individual model was 79%, 74%, 76%, 76%, 76%, and 77%. The model was then combined together and stated the accuracy of 80%. The amalgamation of pretrained CNN was used by Filali et al. [20] to predict skin cancer. As the unwanted features reduces the accuracy, they were removed by adopting feature engineering. The Aujol model used to trim the artifacts by uncovering the object contour. Next, segmented the new object using the otsu algorithm and processed the input image for the CNN. Using the PH2 dataset, the author reported accuracy of 87.8%. A series of Conv2D, BatchNorm and MaxPooling2D CNN models were combined and a new model was proposed by Ly et al. [21]. This new model trained only on a balanced dataset to classify the two stages of skin cancer, accuracy given was 86%.

They utilized a dataset named 'PHDB', with ISIC Archive, Dermnet NZ, and PH2 Training altogether. A two convolutional layers with the kernel size of 5*5 was introduced by E. Nasr-Esfahani et al. [22]. The first and second convolutional layers use 20 and 50 feature maps correspondingly.

Individual convolutional layer followed by pooling layer. Linear transfer function was used in the final decision and the accuracy was 81%. André Esteva et al. [23] refined InceptionV3 network layers by the change in the following parameters, learning rate, damping factor of 0.001 and 16 with all 30 epochs. The model was trained on 129,450 skin lesions collected from various available data sets covering 2,032 different diseases, and it reported 72.1% of accuracy.

III METHODOLOGY

With the advent of processing power and availability of large datasets, the deep learning algorithms were better than human beings. The MobileNet V2, ResNet 152, Inception V3, and Xception are popular models among the available transfer learning techniques to improve the speed and performance.

A. Description of the skin lesion dataset

The dataset used here is HAM10000 (human vs. machine) [24]. It comprises 10015 dermoscopy images and 7 distinct groups. They are: Actinic keratosis (akiec) (327), basal cell carcinoma (bcc) (541), benign keratosis (bkl) (1099), dermatofibroma (df) (155), melanocytic nevi (nv) (6705), melanoma (mel) (1113) and vascular cutaneous lesions (vasc) (142). Figure 1 displays seven types of lesions and Figure 2 depicts their incidence. Lesion type and number were denoted by x axis and y axis respectively. This dataset has divided into three groups called training, testing and validating so there was no difference in the result.

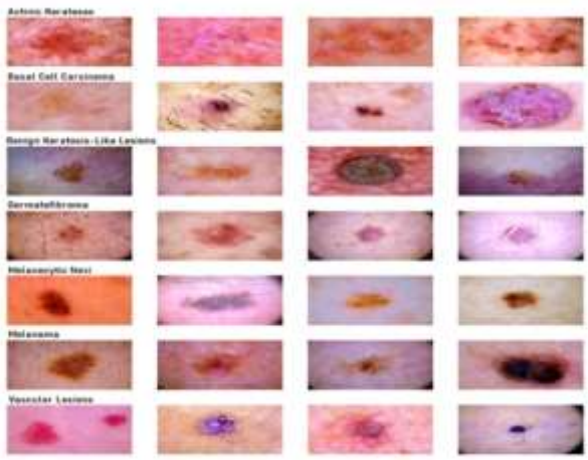

Fig. 1. Seven types of lesions

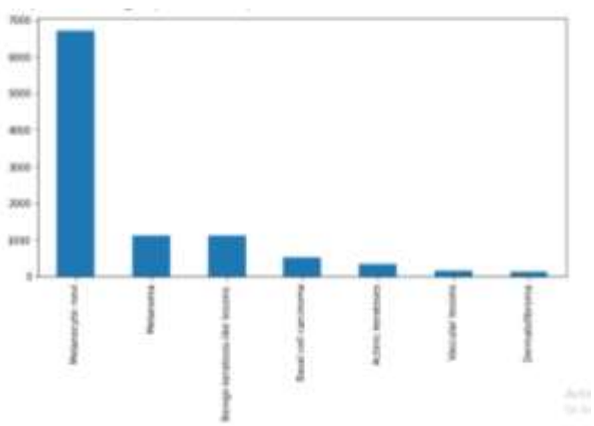

Fig. 2. Distribution of types of lesions

B. Data preparation

Exploratory data analysis done first to detect duplicate images. The validation set was shaped with the split ratio of 83:17 after removing the redundant images. After the splitting, there will be 9077 images and the 938 images in training and validating sets correspondingly. The data augmentation techniques mirroring, cropping, and rotation were applied to get the images with the preferred scale of 224x224 pixels. To retain the propositions between the classes Stratified sampling was applied. The model architecture takes the images from the training set through the preprocessing functions. The architectures need the input images in a specific form and which was achieved by preprocessing functions.

C. Transfer learning network

The transfer learning technique is based on the concept of reusing a model which is specific to a task from some other task. Transfer learning is much required in the situation where the training dataset is not enough but this problem can be rectified by applying data augmentation. As the two types of cancer have common characteristics it takes much time for classification. To ease this process the transfer learning will be used. Similar lesions can be classified efficiently with the help of transfer learning. The last layer only changed according to the dataset in the transfer learning network and it trained on the dataset and weights are fixed.

The models used for comparison are InceptionV3, MobileNet V2, ResNet152 and Xception with base CNN. The fixed weights help the different layers to predict the different types of lesion accurately and they cannot be used as it is. The four transfer learning networks are applied on the dataset and the results are compared to get the best working model.

(1) Inception V3

InceptionV3 [25] is an improvised form of the GoogLeNet architecture [26], which makes the procedure easier and more competent. It resembles a multi stage feature extractor. It computes 3 types of convolution. They are 1x1, 3x3, 5x5 inside the network's same module. The next layer of the network takes stacked outcome of the filters as input.

(2) Xception

The continuation of Inception architecture is Xception [27]. With the help of depth-separable fold, the Xception overtakes the inception in terms of performance. There is no separate spatial correlation for each output channel. It does a depth wise 1x1 convolution to get the correlation for the cross channel. The performance of inception is better for small data and significantly better for large data.

(3) MobileNet V2

This network uses depth separable connections like the Xception network. Each input channel is applied filters individually by the depth wise convolution in MobileNets [28]. The point wise convolution combined the outcome of the aforementioned and one by one convolution.

This is the working of a regular convolutional layer. Here, associate the screened inputs to form a new outcome. A depth separable convolution splits this into 2 layers. One is filtering and the second one is merging. This factorization has the impact of notably decreasing computation and model size. For the mobile and embedding applications, MobileNet is most suitable. When compared to the other model, it has minimum parameters and minimum complexity. MobileNet network structure is a compressed form of Xception network and Inception network.

(4) ResNet 152:

One of the very deep networks is ResNet network. ResNet 152 can have layers upto 152. Residual Networks or ResNets learn residual functions associated with layer inputs instead of learning unreferenced functions. Instead of expecting several stacked layers to all match the desired underlying map directly, residual mesh matches them to the residual map[29]. Stack the remaining blocks on top of each other to form a network. For example, ResNet-80 has 80 layers

	lesion_id	image_id	dx	dx_type	age	sex	localization	dataset
10010	HAM_0002867	ISIC_0033084	akiec	histo	40.0	male	abdomen	vidir_modern
10011	HAM_0002867	ISIC_0033550	akiec	histo	40.0	male	abdomen	vidir_modern
10012	HAM_0002867	ISIC_0033536	akiec	histo	40.0	male	abdomen	vidir_modern
10013	HAM_0000239	ISIC_0032854	akiec	histo	80.0	male	face	vidir_modern
10014	HAM_0003521	ISIC_0032258	mel	histo	70.0	female	back	vidir_modern

Fig.3 Last 5 rows in the dataset

	lesion_id	image_id	dx	dx_type	age	sex	localization	datase
9725	HAM_0004376	ISIC_0024843	akiec	histo	70.0	female	face	rosenda
6059	HAM_0003024	ISIC_0024768	nv	follow_up	35.0	female	trunk	vidir_molem
4540	HAM_0001659	ISIC_0026664	nv	follow_up	35.0	male	lower extremity	vidir_molem
3817	HAM_0004625	ISIC_0029346	nv	follow_up	40.0	male	upper extremity	vidir_molem
7914	HAM_0000443	ISIC_0034271	nv	histo	35.0	female	back	vidir_mode

Fig.4 Sample rows in the dataset

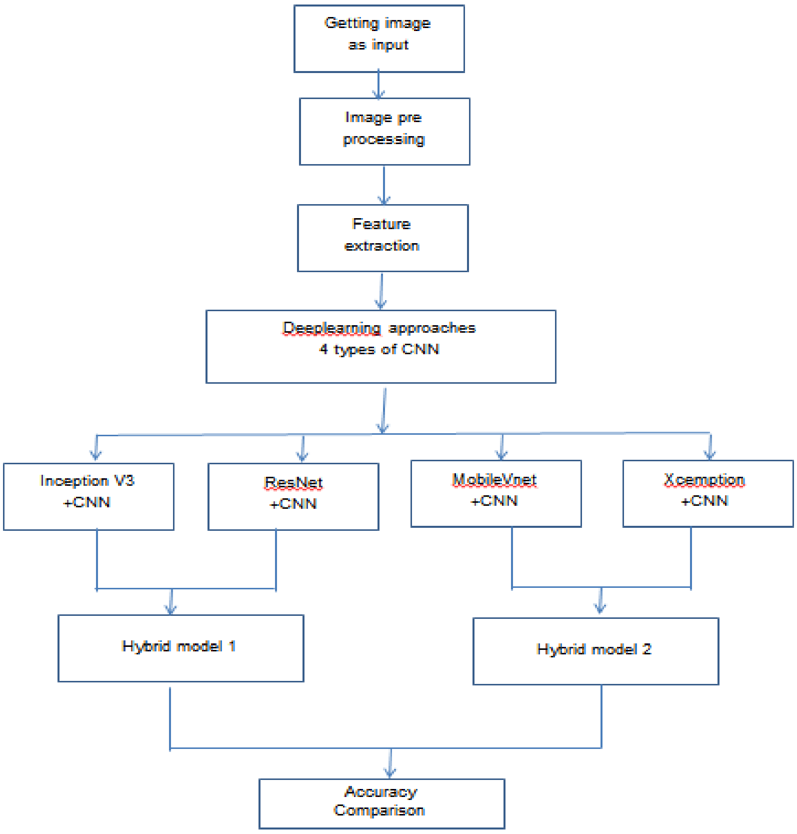

Fig. 5 Proposed Methodology

First the CNN base model is built and results obtained as follows.

	precision	recall	f1-score	support
class 0	0.72	0.46	0.57	28
class 1	0.75	0.50	0.60	48
class 2	0.67	0.52	0.58	93
class 3	0.25	0.25	0.25	8
class 4	0.84	0.95	0.89	534

Fig. 6 Base CNN Model

IV RESULT AND DISCUSSION

Model	Validation		Testing	
	Accuracy	Loss	Accuracy	Loss
MobileNet V2 + CNN	0.75	0.84	0.75	0.83
Inception V3 + CNN	0.73	0.79	0.74	0.79
ResNet152 + CNN	0.80	0.80	0.81	0.88
Xception + CNN	0.81	0.75	0.79	0.82
Hybrid Model 1 (ResNet152 + Inception V3)	0.87	0.44	0.85	0.48
Hybrid Model 2 (MobileNet V3 + Xception)	**0.88**	**0.39**	**0.88**	**0.41**

Table 1: Accuracy and Loss in Validation and Testing in various models

```
def Hybrid(models, model_input):
    outputs = [model.outputs[0] for model in models]
    y = layers.Average()(outputs)
    model = Model(model_input, y, name='Hybrid')
    return model


Hybrid_model = Hybrid([resnet_model, inception_model], model_input)


Hybrid_model.compile(loss='categorical_crossentropy',
                     optimizer=optimizer,
                     metrics=['accuracy'])
```

The following figure depicts the results gained by the above mentioned hybrid model.

```
loss_val, acc_val = Hybrid_model.evaluate(X_val, y_val, verbose=1)

    26/26 [==============================] - 10s 368ms/step - loss: 0.4431 - accuracy: 0.87

print("Validation: accuracy = %f  ;  loss_v = %f" % (acc_val, loss_val))

    Validation: accuracy = 0.875312  ;  loss_v = 0.443082


loss_test, acc_test = Hybrid_model.evaluate(X_test, y_test, verbose=1)
print("Test: accuracy = %f  ;  loss = %f" % (acc_test, loss_test))

    63/63 [==============================] - 24s 381ms/step - loss: 0.4871 - accuracy: 0.85
    Test: accuracy = 0.858211  ;  loss = 0.487124
```

Fig. 7 Loss and Accuracy in the first hybrid model

The second hybrid model is built by combining the two models MobileNet V2 and Xception.

```
def Hybrid(models, model_input):
    outputs = [model.outputs[0] for model in models]
    y = layers.Average()(outputs)
    model = Model(model_input, y, name='Hybrid')
    return model


Hybrid_model = Hybrid([mobilenet_model, xception_model], model_input)


Hybrid_model.compile(loss='categorical_crossentropy',
              optimizer=optimizer,
              metrics=['accuracy'])
```

The below figure demonstrates the outcome of later hybrid model

```
loss_val, acc_val = Hybrid_model.evaluate(X_val, y_val, verbose=1)

    902/902 [==============================] - 368s 408ms/step

print("Validation: accuracy = %f  ;  loss_v = %f" % (acc_val, loss_val))

    Validation: accuracy = 0.888027  ;  loss_v = 0.399892


loss_test, acc_test = Hybrid_model.evaluate(X_test, y_test, verbose=1)
print("Test: accuracy = %f  ;  loss = %f" % (acc_test, loss_test))

    1002/1002 [==============================] - 419s 418ms/step
    Test: accuracy = 0.885230  ;  loss = 0.411560
```

Fig.8 Loss and Accuracy in the second hybrid model

Efficiency assessment components

There are several components that exist to assess the efficiency of proposed model structure. This enclosed accuracy, precision, recall and F1 score. The following equation uses 4 notations. They are FP (a) (False Positive) is a number of positive forecasted instances which are actually negative, FN (b) (False Negative) is a number of falsely forecasted as negative, TP (c) (True Positive) is a number correctly forecasted positive instances , TN (d) (True Negative) is a number of forecasted negative instances [30].

Accuracy: Measures the flawless classified instances.

Acc= (c + d) / (c + d + a + b) *100 ---- (1)

Precision: Ratio of true positive of the model.

Prec = c / (c + a) ----------- (2)

Recall: Measurement of true positive forecast from all possible positive forecast.

Rec= c/ (c + b) ----------- (3)

F1 Score: calculating a weighted average that comprises precision and recall.

F1 − sco = (2 * (Prec * Rec)) / (Prec + Rec) ---(4)

V CONCLUSION

This paper exhibits various transfer learning methods to detect skin cancer. There are six methods that are evaluated based on the accuracy metrics. The methods MobileNet V2 + CNN, Inception V3 + CNN, ResNet152 + CNN, Xception + CNN, Hybrid Model 1 (ResNet152 + Inception V3) and Hybrid Model 2 (MobileNet V3 + Xception) were evaluated and they produced accuracy of 75%, 74%, 81%, 79%, 85% and 88% respectively. Hence the second hybrid model is the better approach compared to others, in detecting skin cancer.

REFERENCES

1. Factors, R. Basal and Squamous Cell Skin Cancer Causes, Risk Factors, and Prevention. 2019. Available online: https://www. cancer.org/content/dam/CRC/PDF/Public/8819.00.pdf (accessed on 2 March 2022).
2. Skin Cancer. Available online: https://www.aad.org/media/stats-skin-cancer (accessed on 22 May 2022).
3. Incidence estimate of nonmelanoma skin cancer (keratinocyte carcinomas) in the US population, 2012. JAMA Dermatol. 2015, 151, 1081–1086. [CrossRef] [PubMed]
4. Whiteman, D.C.; Green, A.C.; Olsen, C.M. The growing burden of invasive melanoma: Projections of incidence rates and numbers of new cases in six susceptible populations through 2031. J. Investig. Dermatol. 2016, 136, 1161–1171. [CrossRef] [PubMed]
5. Xie, F.; Fan, H.; Li, Y.; Jiang, Z.; Meng, R.; Bovik, A. Melanoma classification on dermoscopy images using a neural network ensemble model. IEEE Trans. Med. Imaging 2016, 36, 849–858. [CrossRef] 8. Dalila, F.; Zohra, A.; Reda, K.; Hocine, C. Segmentation and classification of melanoma and benign skin lesions. Optik 2017, 140, 749–761. [CrossRef]
6. Cancer Stat Facts: Melanoma of the Skin. Available online: https://seer.cancer.gov/statfacts/html/melan.html (accessed on 22 May 2022).
7. Melanoma: Statistics. Available online: https://www.cancer.net/cancer-types/melanoma/statistics (accessed on 22 May 2022).
8. Kato, J.; Horimoto, K.; Sato, S.; Minowa, T.; Uhara, H. Dermoscopy of melanoma and non-melanoma skin cancers. Front. Med. 2019, 6, 180. [CrossRef]
9. Gershenwald, J.E.; Scolyer, R.A.; Hess, K.R.; Sondak, V.K.; Long, G.V.; Ross, M.I.; Lazar, A.J.; Faries, M.B.; Kirkwood, J.M.; McArthur, G.A.; et al. Melanoma staging: Evidence-based changes in the American Joint Committee on Cancer eighth edition cancer staging manual. CA Cancer J. Clin. 2017, 67, 472–492. [CrossRef]
10. Ibrahim, H.; El-Taieb, M.; Ahmed, A.; Hamada, R.; Nada, E. Dermoscopy versus skin biopsy in diagnosis of suspicious skin lesions. Al-Azhar Assiut Med. J. 2017, 15, 203. [CrossRef]
11. Bajwa, M.N.; Muta, K.; Malik, M.I.; Siddiqui, S.A.; Braun, S.A.; Homey, B.; Dengel, A.; Ahmed, S. Computer-aided diagnosis of skin diseases using deep neural networks. Appl. Sci. 2020, 10, 2488. [CrossRef]
12. Carrera, C.; Marchetti, M.A.; Dusza, S.W.; Argenziano, G.; Braun, R.P.; Halpern, A.C.; Jaimes, N.; Kittler, H.J.; Malvehy, J.; Menzies, S.W.; et al. Validity and reliability of dermoscopic criteria used to differentiate nevi from melanoma: A web-based international dermoscopy society study. JAMA Dermatol. 2016, 152, 798–806. [CrossRef] [PubMed]
13. Lynn, N.C.; War, N. Melanoma classification on dermoscopy skin images using bag tree ensemble classifier. In Proceedings of the 2019 International Conference on Advanced Information Technologies (ICAIT), Yangon, Myanmar, 6–7 November 2019; pp. 120–125.
14. Pham, T.C.; Luong, C.M.; Visani, M.; Hoang, V.D. Deep CNN and data augmentation for skin lesion classification. In Asian Conference on Intelligent Information and Database Systems; Springer: Berlin/Heidelberg, Germany, 2018; pp. 573–582.
15. Yu, L.; Chen, H.; Dou, Q.; Qin, J.; Heng, P.A. Automated melanoma recognition in dermoscopy images via very deep residual networks. IEEE Trans. Med. Imaging 2016, 36, 994–1004. [CrossRef]
16. Yu, Z.; Jiang, X.; Zhou, F.; Qin, J.; Ni, D.; Chen, S.; Lei, B.; Wang, T. Melanoma recognition in dermoscopy images via aggregated deep convolutional features. IEEE Trans. Biomed. Eng. 2018, 66, 1006–1016. [CrossRef]
17. Brinker, T.J.; Hekler, A.; Enk, A.H.; Berking, C.; Haferkamp, S.; Hauschild, A.; Weichenthal, M.; Klode, J.; Schadendorf, D.; Holland-Letz, T.; et al. Deep neural networks are superior to dermatologists in melanoma image classification. Eur. J. Cancer 2019, 119, 11–17. [CrossRef]

18. Han, S.S.; Kim, M.S.; Lim, W.; Park, G.H.; Park, I.; Chang, S.E. Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. J. Investig. Dermatol. 2018, 138, 1529–1538. [CrossRef] [PubMed]
19. Aldwgeri A., Abubacker N.F. (2019) Ensemble of Deep Convolutional Neural Network for Skin Lesion Classification in Dermoscopy Images. In: Badioze Zaman H. et al. (eds) Advances in Visual Informatics. IVIC 2019. Lecture Notes in Computer Science, vol 11870. Springer, Cham. https://doi.org/10.1007/978-3-030-34032-2_20
[20] Filali, Y., Khoukhi, E.L., Sabri, M.A., Aarab, A., et al.: Efficient fusion of handcrafted and pretrained CNNs features to classify melanoma skin cancer. Multimed. Tools Appl. 79, 31219 31238 (2020). https:// doi. org/ 10. 1007/ s11042- 020- 09637-4
[21] P. Ly, D. Bein and A. Verma, "New Compact Deep Learning Model for Skin Cancer Recognition," 2018 9th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), 2018, pp. 255-261, doi: 10.1109/UEMCON.2018.8796628.
[22] E. Nasr-Esfahani et al., "Melanoma detection by analysis of clinical images using convolutional neural network," 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2016, pp. 1373-1376, doi: 10.1109/EMBC.2016.7590963.
[23] Esteva, A., Kuprel, B., Novoa, R. et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 542, 115–118 (2017). https://doi.org/10.1038/nature21056
24. Maheshwari K., Shaha A., Arya D., Rajasekaran R., Tripathy B.K. Deep Learning: Research and Applications. In: Siddhartha B., Vaclav S., Aboul Ella H., Satadal S., Tripathy B.K., editors. *Convolutional Neural Networks: A Bottom-Up Approach.* De Gruyter; Berlin, Germany: 2020. pp. 21–50. [CrossRef] [Google Scholar]
25. Szegedy C., Vanhoucke V., Ioffe S., Shlens J., Wojna Z. Rethinking the Inception Architecture for Computer Vision; Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); Las Vegas, NV, USA. 27–30 June 2016; pp. 2818–2826. [Google Scholar]
26. Szegedy C., Wei L., Yangqing J., Sermanet P., Reed S., Anguelov D., Erhan D., Vanhoucke V., Rabinovich A. Going deeper with convolutions; Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); Boston, MA, USA. 7–12 June 2015; pp. 1–9. [Google Scholar]
27. Chollet F. Xception: Deep Learning with Depthwise Separable Convolutions; Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); Honolulu, HI, USA. 21–26 July 2017; pp. 1800–1807. [Google Scholar]
28. Howard A.G., Zhu M., Chen B., Kalenichenko D., Wang W., Weyand T., Andreetto M., Adam H. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv.* 20171704.04861 [Google Scholar]
29. He, K., Zhang, X., Ren, S. & Sun, J. Deep residual learning for image recognition. in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition 770–778 (2016).
30. Liu, Yangguang & Zhou, Yangming & Wen, Shiting & Tang, Chaogang. (2014). A Strategy on Selecting Performance Metrics for Classifier Evaluation. International Journal of Mobile Computing and Multimedia Communications. 6. 20-35. 10.4018/IJMCMC.2014100102