International Journal of Scientific Research in Computer Science, Engineering and Information Technology
ISSN : 2456-3307 (www.ijsrcseit.com)
doi : https://doi.org/10.32628/CSEIT228661

A Review on Transfer Learning Approaches for Skin Melanoma Classification

Arti Pandey[*1], Dr. Sheshang Degadwala[2], Dhairya Vyas[3]
[*1]Computer Engineering Department, Sigma Institute of Engineering, Vadodara, Gujarat, India
[2]Computer Engineering Department, Sigma Institute of Engineering, Vadodara, Gujarat, India
[3]Managing Director, Shree Drashti Infotech LLP, Vadodara, Gujarat, India

Article Info

Publication Issue :
Volume 8, Issue 6
November-December-2022

Page Number : 394-399

Article History
Accepted: 20 Nov 2022
Published: 05 Dec 2022

ABSTRACT

Skin is important organ of our body which covers muscles, bones, and other parts of body. Melanoma is a kind of skin cancer that begins in melanocytes cell. It can influence on the skin only, or it may expand to the bones and organs. It is less common, but more serious and aggressive than other types of skin cancer. Majority of deaths related to skin cancer occur due to Melanoma over the world. For effective treatment it is very important to melanoma identified earlier as possible. As well as detection of the stages of melanoma to recognize depth of spreading of melanocyte cell in other organ of body. Process of Detection of Skin cancer is difficult, expensive, and time-consuming process. Purpose of this research review is to more accurate recognition the types of Melanomas and decrease ratio of false diagnosis using transfer learning model for melanoma classification using AlexNet, VggNet and ResNet. The working of the different transfer learning model, its pros. and cons. Are discuss in this paper.

Keywords: Skin Melanoma, Transfer Learning, AlexNet, VggNet, ResNet.

I. INTRODUCTION

Today's Many people are affected by skin cancer in worldwide. That may lead to death due to skin cancer. Over 3.5 million cases of Melanoma, Basal Cell Carcinoma and Squamous Cell Carcinoma are diagnosed every year. [1-5] The cancer like lung cancer, brain tumor, breast cancer, colon cancer is diagnosis earlier by CT scan, MRI etc. But skin cancer is very difficult to identify because skin lesions look quite like each other. So, the people are simply ignoring it. But it may lead to skin cancer. [7] Detection of skin cancer in the early stages is a difficult and expensive process. [2]

The Skin cancer is the most aggressive of all cancer types.[1] Skin cancer is caused due to uncontrolled growth of skin cells.[2] These abnormal cells have an ability to spread to other body parts.[4] This cancer is generally observed on the skin area which is more exposed to the sun.[5]

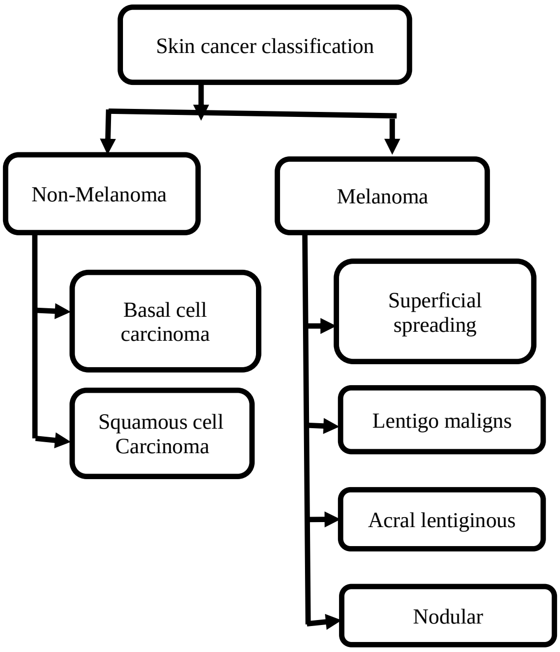

Figure 1. Skin Cancer Types

People with fair skinned who has chances of Melanoma occurrences is more as compared to dark skinned people. Melanoma occurs more in women as compared to men. Mostly occurred in legs, finger in women or back of men.[17] In India, period of 2008 to 2018 ratio melanoma in men is higher than females. Age under 49 death ratio is 64 % in women than men. People diagnosed of melanoma in men of fair skin of age 50 year and older people have more twice as compared to women. U.S. A has more death ratio than other country due to melanoma which is 9320 in 2018.In past decade (2008-2018), melanoma patients will increase by 53% annually. Ratio of occurring melanoma of increases due to skin more influenced by sun rays, UV radiation from sunshine or tanning beds which cause sunburns. Melanoma is curable disease if it is recognized earlier [3]. Earlier diagnosis and timely treatment lead to decrease death of Melanoma patients by 93% [4]. According to Medical records, Skin Cancer is curable dieses if it is detected in early Stages [1]. Early detection techniques of Melanoma, such as computerized skin cancer diagnostic system is more efficient and less cost and less time consuming. Organ transplant patients has more risk melanoma than general people.

II. LITERATURE STUDY

Sr. No.	Paper Title	Publication-Year	Methods Use	Advantages	Future Work
1	Skin Cancer Disease Detection Using Transfer Learning Technique	MDPI-2022	MobileNetV2	Data augmentation techniques were used to increase the dataset's size and improve the accuracy Of MobileNetV2.	Model training from scratch to improve model Efficiency.
2	Machine learning approach in melanoma cancer stage detection	ScienceDirect-2020	SVM, CNN, CNN + Similarity Measure for Text Processing	It gives Sensitivity 96.03% and Specificity 96.33%	Shape, Color features takes time to calculate so, use deep features to make system fast.
3	Multi-Class Skin Lesion Detection and Classification via Teledermatology	IEEE-2021	CNN, high dimension contrast transform (HDCT)	Saliency approach for the lesion segmentation and achieved an accuracy of 94.92% on the ISBI2016 dataset.	Improve the segmentation accuracy using the Mask RCNN.

4	An Enhanced Transfer Learning Based Classification for Diagnosis of Skin Cancer	MDPI-2022	VGG-16	Overall accuracy of 89.09% on 128 batch size with Adam optimizer and 10 epochs.	It can be enhanced by increasing both true positives as well as true Negatives simultaneously
5	Skin Lesion Classification by Ensembles of Deep Convolutional Networks and Regularly Spaced Shifting	IEEE-2021	MobileNet GoogleNet	Considered multiple shifted versions of the test input image so that the shift vectors form a regular lattice.	Testing of more deep networks and other topologies of the lattice.
6	Dermoscopy Image Classification Based on StyleGAN and DenseNet201	IEEE-2020	StyleGAN DenseNet201	Improved intraclass-imbalanced datasets using StyleGAN Which Generate Images.	Stage Classification introducing the attention mechanism to a skin lesion image synthesis and classification Model
7	Performance of Multi-Layer Perceptron and Deep Neural Networks in Skin Cancer Classification	IEEE-2021	CNN, VGG-16	Work with large dataset HAM10000	Stage or multi-Classification can be done for future direction research.
8	Automated Diagnosis of Skin Cancer for Healthcare: Highlights and Procedures	IEEE-2021	ANN, SVM, MLR, LWL	Feature selection methods aiming to decrease intra-class variance and increase the inter-class separation, which improves the classification.	ML approaches takes time as feature extraction and classification are two separate stage so need to work on deep learning methods.
9	Skin cancer classification using Convolutional neural networks	IEEE-2020	CNN	CNN model to detect skin cancer with an accuracy of >80%	Train with more deep transfer learing networks.
10	Skin Cancer Classification Using Image Processing and Machine Learning	IEEE-2021	OTSU, HOG, GLCM Random Forest	Accuracy using Random Forest classifier on ISIC-ISBI 2016 is 93.89%	Dataset is two small work on binary class only.
11	Automatic Segmentation of Melanoma Skin Cancer Using Deep Learning	IEEE-2020	U-net	U-net network proved to be highly effective even with small datasets. Accuracy is 92.3%.	Complex Architecture hard to learn and implement.
12	A Comparison of Neural Network Approaches for Melanoma Classification	IEEE-2020	SVM, CNN, ResNet, VggNet	The ResNet obtained an AUC equal to 87.5%.	In future possible technique can exploit a class-to-class distance measurement to select the more feasible classification.

III. METHODS AND MATERIAL

A. Resnet [2,10]

ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. It is a construction piece that was destroyed but which still contains a bridged connector (formerly known as a legacy connection) that permits data to flow through it without being altered in any way despite the destruction. The data signal x is converted into an output signal F by the activation curve layer. It is composed of two types: layer 1 and layer 2, which are interconnected (x). The transfer seems to be comparable to those of a connection that has been skipped in this instance. The residual unit in this specific design demonstrates how it control signal x varies from those of the thanks to advances F, which is a result of the construction process itself (x). In accordance with the findings of this study, if the infrastructure has also fruitfully recreated the linear mapping that is assembled on a given spot, the improvements may be effective to minimize muscular endurance in the unavailable slabs on varying scales to essentially zero, but also guarantee that the output passes across the disconnect with next to no damage.

The ResNet architecture follows two basic design rules. First, the number of filters in each layer is the same depending on the size of the output feature map. Second, if the feature map's size is halved, it has double the number of filters to maintain the time complexity of each layer. ResNet-50 has an architecture based on the model depicted above, but with one important difference. The 50-layer ResNet uses a bottleneck design for the building block. A bottleneck residual block uses 1×1 convolutions, known as a "bottleneck", which reduces the number of parameters and matrix multiplications. This enables much faster training of each layer. It uses a stack of three layers rather than two layers.

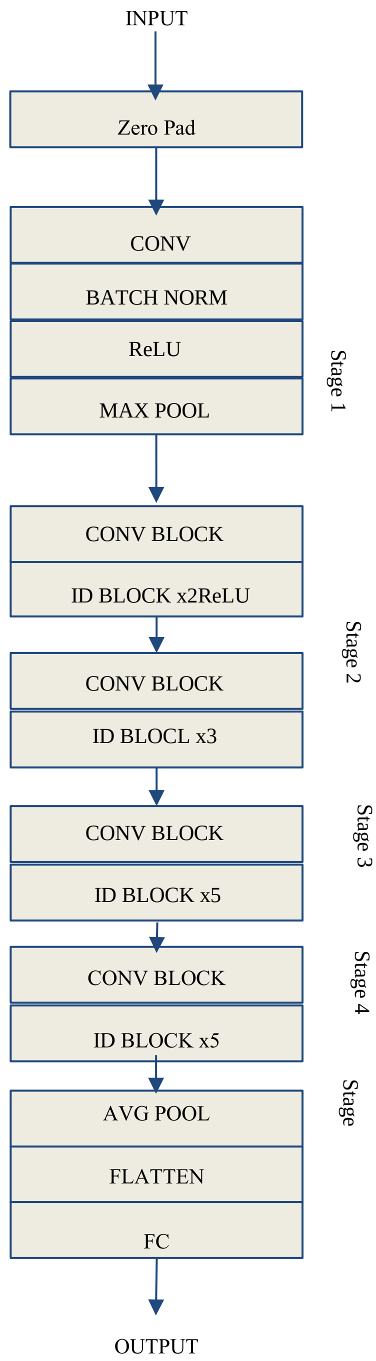

Figure 2. ResNet Model Layers

B. VGGNet [1,10]

The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, centre). In one of the configurations, it also utilizes 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e., the padding is 1-pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2-pixel window, with stride 2. Three Fully Connected (FC) layers follow a stack of convolutional layers (which has a different depth in different architectures): the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks.

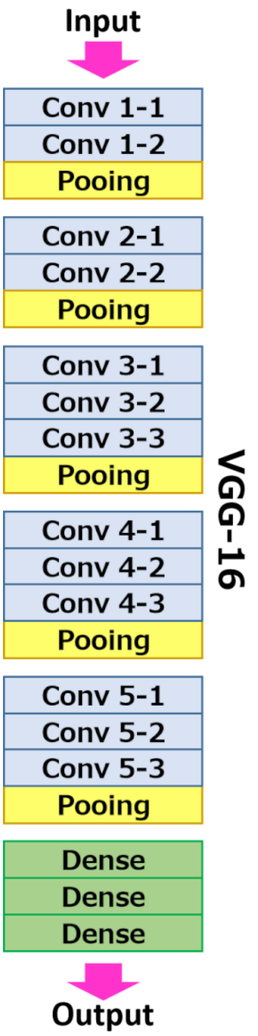

Figure 4. Vgg-16 Model Layers

All hidden layers are equipped with the rectification (ReLU) non-linearity. It is also noted that none of the networks (except for one) contain Local Response Normalisation (LRN), such normalization does not improve the performance on the ILSVRC dataset but leads to increased memory consumption and computation time.

C. AlexNet [1,5]

A large perceptron (RNN) may be able to achieve high excellent on a highly difficult dataset by using solely supervised learning methodologies, according to the findings of the AlexNet study. In the year after the debut of AlexNet, a competition was launched that has continued to this day.

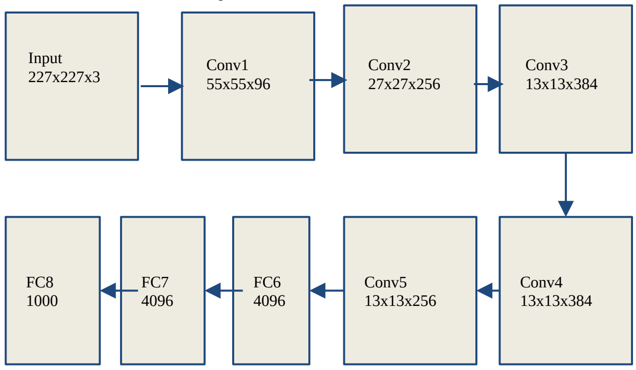

Figure 4. AlexNet Model Layers

The Convolutional Neural Network is used to categories all contributions to the ImageNet database. CNN is a pioneer in biomedical research, ushering in a new age with AlexNet, which was created in collaboration with the National Institutes of Health and launched in 2004. Because a variety of deep learning are readily available, the mounting of AlexNet is rather basic.

IV. Comparative Analysis

TABLE I
COMPARATIVE ANALYSIS

Method	Pros.	Cons.
ResNet [2]	It is possible to skip connections. It makes use of batch normalization to boost efficiency while maintaining accuracy.	Implementation is time-consuming.
AlexNet [5]	Unlike a convolutional layer, which depends on local spatial coherence and a narrow receiving field, a fully connected layer learns features from all the combinations of the features of the preceding layer.	Complicated layers with many connections are very computationally costly to create.
VggNet	It only contains 80	Accuracy

[1,5,10]	percent of the whole number of parameters.	decreases in a very progressive manner.

V. CONCLUSION

Melanoma detection early stages is very difficult and time-consuming process. Computer aided system uses past information based on that information it may identify the melanoma. accuracy of diagnosis melanoma. To overcome problem of false diagnosis by unexperienced doctors may lead to increase survival rate of melanoma patients.

In Future when it comes to classifying skin melanoma classes depending on sub types of images transfer learning model perform better than other CNN models. In different models fine-tuning perform better than traditional CNN layers, by utilising the RESNET or ALEXNET transfer learning technique.

VI. REFERENCES

[1] O. Sharif, M. M. Hoque, A. S. M. Kayes, R. Nowrozy, and I. H. Sarker, "Skin Cancer Disease Detection Using Transfer Learning Technique" sciences Learning Techniques,pp. 1–23, 2020.

[2] R. Patil and S. Bellary, "Machine learning approach in melanoma cancer stage detection," J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 6, pp. 3285–3293, 2022, doi: 10.1016/j.jksuci.2020.09.002.

[3] M. A. Khan, K. Muhammad, M. Sharif, T. Akram, and V. H. C. D. Albuquerque, "Multi-Class Skin Lesion Detection and Classification via Teledermatology," IEEE J. Biomed. Heal. Informatics, vol. 25, no. 12, pp. 4267–4275, 2021, doi: 10.1109/JBHI.2021.3067789.

[4] V. Anand, S. Gupta, A. Altameem, S. R. Nayak, R. C. Poonia, and A. K. J. Saudagar, "An Enhanced Transfer Learning Based Classification for Diagnosis of Skin Cancer," Diagnostics, vol. 12, no. 7, 2022, doi: 10.3390/diagnostics12071628.

[5] K. Thurnhofer-Hemsi, E. Lopez-Rubio, E. Dominguez, and D. A. Elizondo, "Skin lesion classification by ensembles of deep convolutional networks and regularly spaced shifting," IEEE Access, vol. 9, pp. 112193–112205, 2021, doi: 10.1109/ACCESS.2021.3103410.

[6] C. Zhao, R. Shuai, L. Ma, W. Liu, Di. Hu, and M. Wu, "Dermoscopy Image Classification Based on StyleGAN and DenseNet201," IEEE Access, vol. 9, pp. 8659–8679, 2021, doi: 10.1109/ACCESS.2021.3049600.

[7] Y. Jusman, I. M. Firdiantika, D. A. Dharmawan, and K. Purwanto, "Performance of multi layer perceptron and deep neural networks in skin cancer classification," LifeTech 2021 - 2021 IEEE 3rd Glob. Conf. Life Sci. Technol., no. LifeTech, pp. 534–538, 2021, doi: 10.1109/LifeTech52111.2021.9391876.

[8] M. A. Wahba and A. S. Ashour, "Automated Diagnosis of Skin Cancer for Healthcare: Highlights and Procedures," Eng. Technol. Healthc., pp. 187–212, 2021, doi: 10.1002/9781119644316.ch10.

[9] C. K. Chin, D. A. Binti Awang Mat, and A. Y. Saleh, "Skin Cancer Classification using Convolutional Neural Network with Autoregressive Integrated Moving Average," ACM Int. Conf. Proceeding Ser., pp. 18–22, 2021, doi: 10.1145/3467691.3467693.

[10] A. Javaid, M. Sadiq, and F. Akram, "Skin Cancer Classification Using Image Processing and Machine Learning," Proc. 18th Int. Bhurban Conf. Appl. Sci. Technol. IBCAST 2021, pp. 439–444, 2021, doi: 10.1109/IBCAST51254.2021.9393198.

[11] R. L. Araújo, F. H. D. d. Araújo, and R. R. V. e. Silva, "Automatic segmentation of melanoma skin cancer using transfer learning and fine-tuning," Multimed. Syst., vol. 28, no. 4, pp. 1239–1250, 2022, doi: 10.1007/s00530-021-00840-3.

[12] M. Frasca, M. Nappi, M. Risi, G. Tortora, and A. A. Citarella, "A comparison of neural network approaches for melanoma classification," Proc. - Int. Conf. Pattern Recognit., pp. 2110–2117, 2020, doi: 10.1109/ICPR48806.2021.9412893.

Cite this Article

Arti Pandey, Dr. Sheshang Degadwala, Dhairya Vyas, "A Review on Transfer Learning Approaches for Skin Melanoma Classification", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 8 Issue 6, pp. 394-399, November-December 2022. Available at doi : https://doi.org/10.32628/CSEIT228661

Journal URL : https://ijsrcseit.com/CSEIT228661