Skin Cancer Classification Using Pre-trained Deep Learning Model

J. ANDREW, VARUN UNNIKRISHNAN NAIR, K. MARTIN SAGAYAM, MOHD HELMY, NOR'AISAH

Key Objectives

- Creating a deep learning model using CNN to classify skin cancer images.
- Using different performance metrics to analyse the model accuracy.
- Compare the results of final, completely implemented model with results in other research papers.

Literature Survey

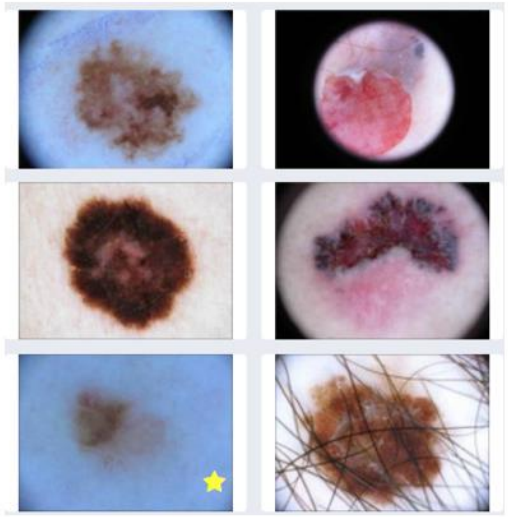
Reference	Accuracy	Specificity	Sensitivity	Research Focus
[1]	79.5%	-	-	Classification of skin lesions
[2]	93.64%	55.18%	92.1%	Skin mole lesion classification.
[3]	81.33%	-	-	Classification of skin lesions
[4]	62.5%	88%	58%	Skin Imaging Collaboration. Verifying the accuracy of the automated systems with the dermatologist's manual
[5]	95.4%	-	-	Skin cancer diagnosing from dermatologic spots
[6]	82.95%	81.5%	89%	AI based skin cancer classification
[7]	65% for melanoma	89.2	98.8	CNN based skin cancer classification
[8]	77% - 81%	-	-	CNN based Skin lesion diagnosis
[9]	96.86%	96.9%	96.9%	Classification of skin lesions through pretrained networks
[10]	98.7%	-	-	k-means technique for skin cancer detection
[11]	85%	-	-	Machine learning and image processing techniques of skin cancer detection
[12]	98.89	86.6%	86.6%	Deep learning based skin cancer detection

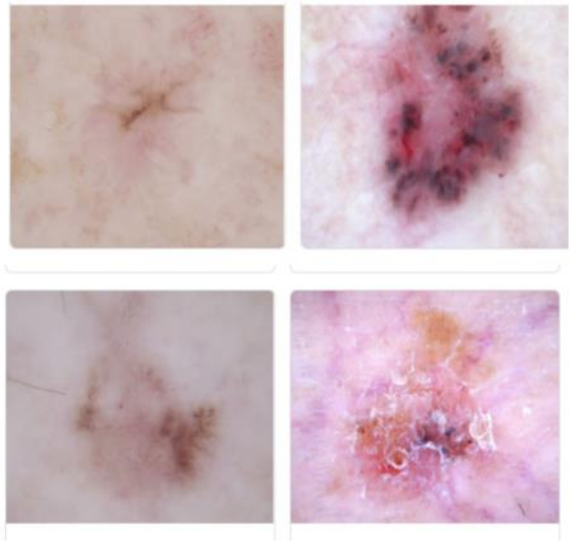
Dataset Details

- The dataset used in the initial implementation was from the ISIC (International Skin Imaging Collaboration) .
- Main goal for them was to reduce melanoma related deaths by providing verified sources of data about all kinds of skin images. Cancerous and non-cancerous.

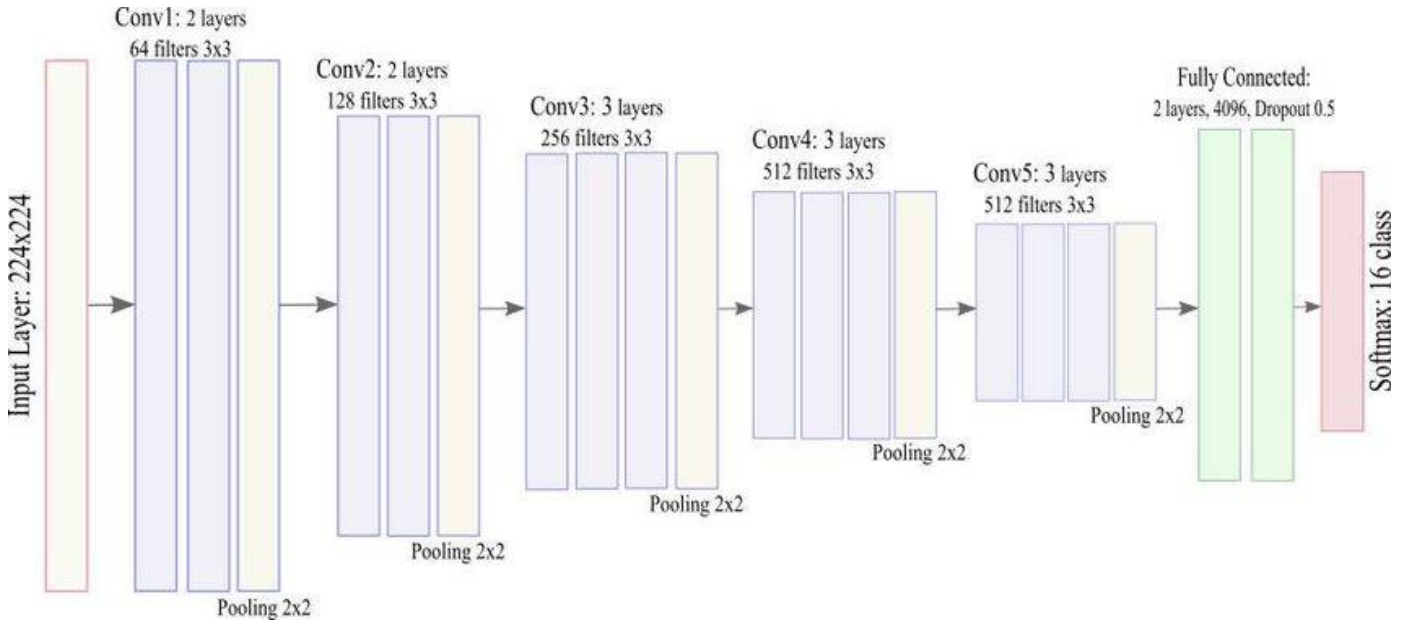
- The dataset was first segregated and structed in a tree format.
- then function flow_from_directory() reads from the passed argument directory and automatically identifies subfolders as classes and content as images.

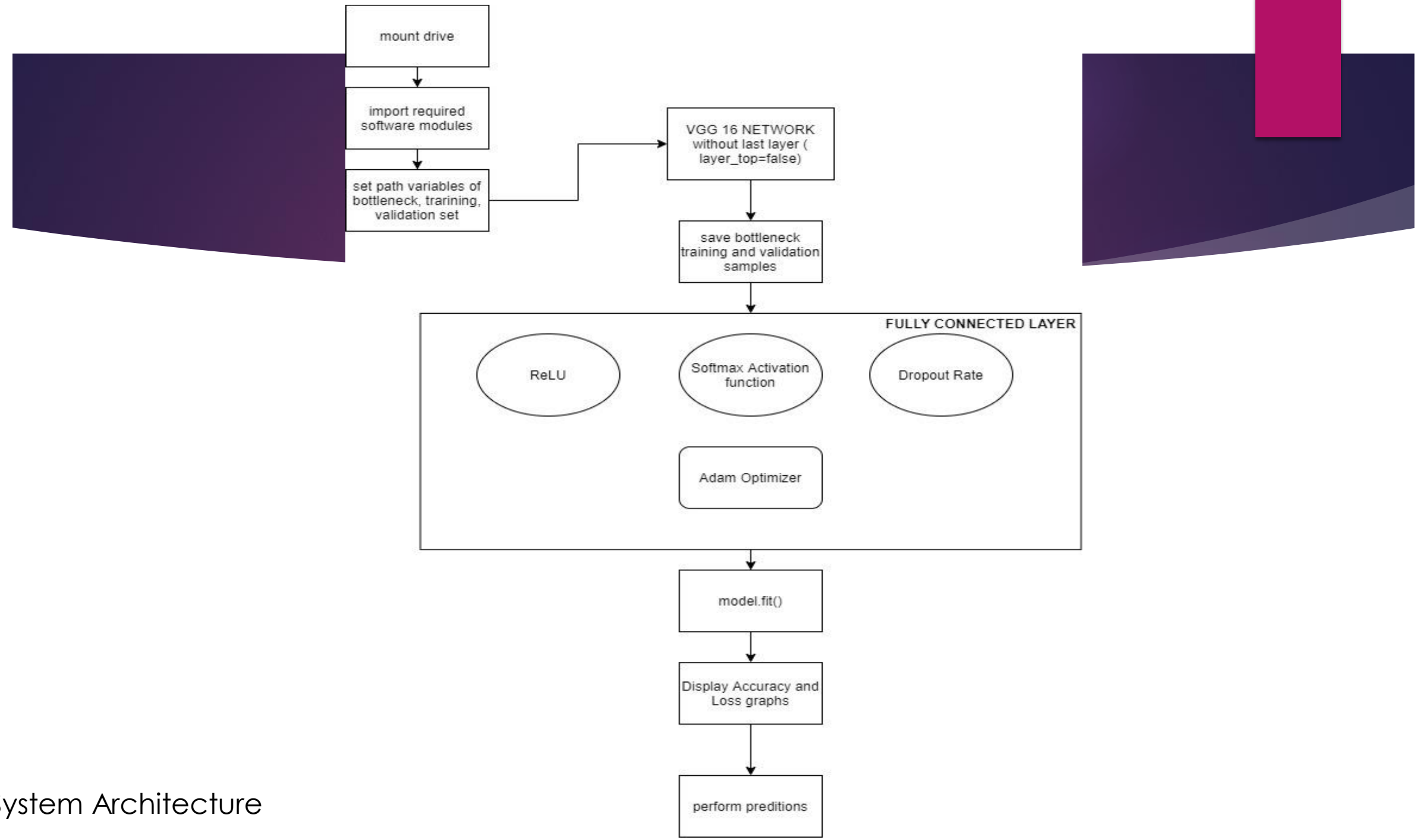
Dataset Details





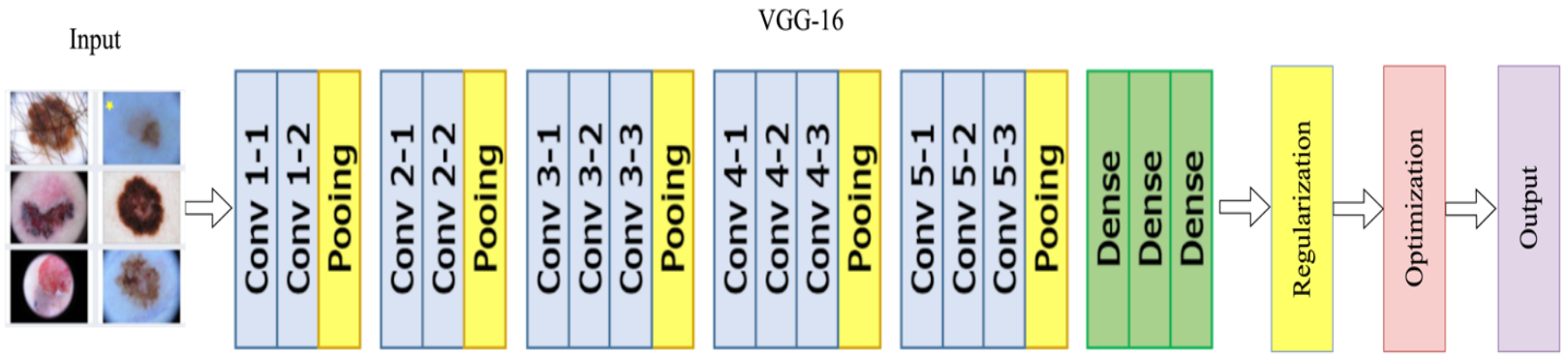
IMPLEMENTED MODULE





System Architecture

Proposed Skin Cancer Classification Model Architecture



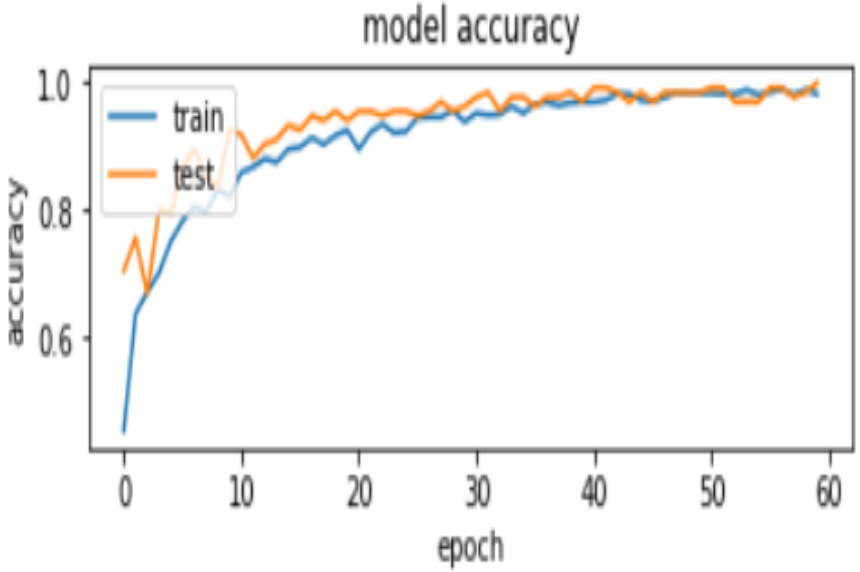
Activation function and Fully Connected layer used in CNN

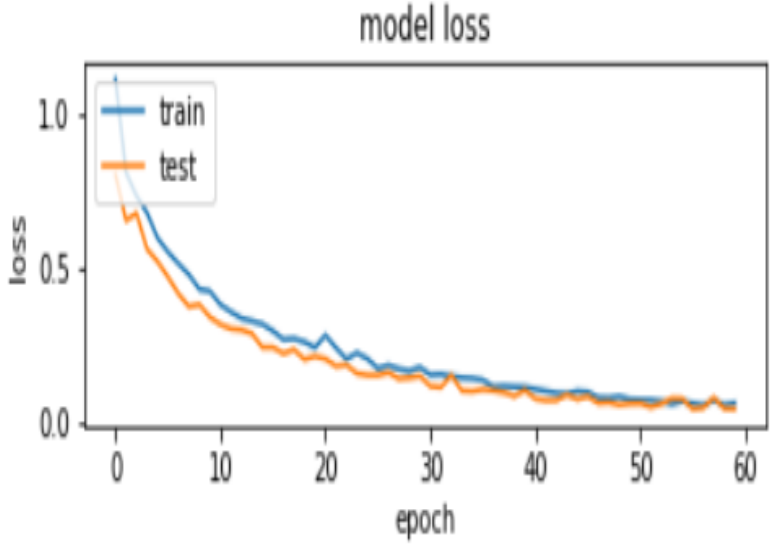
- ReLU- rectified linear unit
- Softmax
- Flatten out(Flattening is converting the data into a 1-dimensional array for inputting it to the next layer) and follow up with fully connected layer 256 output neurons.
- Dropout rate

Adam Optimizer

- Adam can be looked at as a combination of RMSprop and Stochastic Gradient Descent with momentum. It uses the squared gradients to scale the learning rate like RMSprop and it takes advantage of momentum by using moving average of the gradient instead of gradient itself like SGD with momentum. Let's take a closer look at how it works.
- Adam is an adaptive learning rate method, which means, it computes individual learning rates for different parameters. Its name is derived from adaptive moment estimation, and the reason it's called that is because Adam uses estimations of first and second moments of gradient to adapt the learning rate for each weight of the neural network.

Experimental Results





Performance evaluation of the proposed model.

Reference	Accuracy	Specificity	Sensitivity
Pomponiu et al. [20]	93.64 %	55.18 %	92.1 %
Hekler et al. [18]	82.95 %	81.5 %	89 %
Maron et al. [19]	65 %	89.2 %	98.8 %
Our Model	97.2 %	96.5 %	98.2%

Conclusion

- Skin cancer is one of the major diseases prevailing and millions of humans are expected to diagnosed.
- Early detection of malignancy in the skin lesions can greatly reduce the mortality rate and for successful treatments.
- a deep learning based skin cancer classification model is proposed based on pretrained models. VGG-16 model is utilized and trained with skin lesion images.
- The proposed model is focused to detect and classify three major types of skin cancer a)melanoma, (b) basal cell carcinoma, and (c) squamous cell carcinoma.
- The model is experimented with commonly available skin cancer datasets and performance of the model is evaluated based on accuracy, specificity, and sensitivity.
- Experimental and performance analysis shows that the proposed model is performing better compared to the state-of-the-art deep learning techniques.

References

- [1] "CDC - Expected New Cancer Cases and Deaths in 2020." [Online]. Available: https://www.cdc.gov/cancer/dcpc/research/articles/cancer_2020.htm. [Accessed: 02-Jun-2020].
- [2] M. Saraiya *et al.*, "Skin cancer screening among U.S. adults from 1992, 1998, and 2000 National Health Interview Surveys," *Prev. Med. (Baltim).*, vol. 39, no. 2, pp. 308–314, Aug. 2004.
- [3] "Skin Cancer: Melanoma, Basal Cell and Squamous Cell Carcinoma." [Online]. Available: https://www.webmd.com/melanoma-skin-cancer/melanoma-guide/skin-cancer#1. [Accessed: 01-Jun-2020].
- [4] "Ultraviolet (UV) radiation and skin cancer." [Online]. Available: https://www.who.int/news-room/q-a-detail/ultraviolet-(uv)-radiation-and-skin-cancer. [Accessed: 01-Jun-2020].
- [5] J. Andrew, R. Fiona, and H. Caleb Andrew, "Comparative study of various deep convolutional neural networks in the early prediction of cancer," in *2019 International Conference on Intelligent Computing and Control Systems, ICCS 2019*, 2019, pp. 884–890.
- [6] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, "A survey of deep neural network architectures and their applications," *Neurocomputing*, vol. 234, pp. 11–26, Apr. 2017.
- [7] A. Dascalu and E. O. David, "Skin cancer detection by deep learning and sound analysis algorithms: A prospective clinical study of an elementary dermoscope," *EBioMedicine*, vol. 43, pp. 107–113, May 2019.
- [8] "Man against machine: AI is better than dermatologists at diagnosing skin cancer -- ScienceDaily." [Online]. Available: https://www.sciencedaily.com/releases/2018/05/180528190839.htm. [Accessed: 01-Jun-2020].
- [9] J. Andrew, M. Dlvyavarshini, P. Barjo, and I. Tigga, "Spine Magnetic Resonance Image Segmentation Using Deep Learning Techniques," in *2020 6th International Conference on Advanced Computing and Communication Systems, ICACCS 2020*, 2020, pp. 945–950.
- [10] T. J. Brinker *et al.*, "Deep neural networks are superior to dermatologists in melanoma image classification," *Eur. J. Cancer*, vol. 119, pp. 11–17, Sep. 2019.

References

- [11] J. Kawahara, A. Bentaieb, and G. Hamarneh, "Deep features to classify skin lesions," in *Proceedings - International Symposium on Biomedical Imaging*, 2016, vol. 2016-June, pp. 1397–1400.
- [12] T. Y. Tan, L. Zhang, C. P. Lim, B. Fielding, Y. Yu, and E. Anderson, "Evolving Ensemble Models for Image Segmentation Using Enhanced Particle Swarm Optimization," *IEEE Access*, vol. 7, pp. 34004–34019, 2019.
- [13] M. A. Kadampur and S. Al Riyaee, "Skin cancer detection: Applying a deep learning based model driven architecture in the cloud for classifying dermal cell images," *Informatics Med. Unlocked*, vol. 18, p. 100282, Jan. 2020.
- [14] S. Targ, D. Almeida, and K. Lyman, "Resnet in Resnet: Generalizing Residual Architectures," Mar. 2016.
- [15] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning," Feb. 2017.
- [16] G. Huang, S. Liu, L. Van Der Maaten, and K. Q. Weinberger, "CondenseNet: An Efficient DenseNet using Learned Group Convolutions," 2018.
- [17] J. Sanchez, N. Soltani, P. Kulkarni, R. V. Chamarthi, and H. Tabkhi, "A reconfigurable streaming processor for real-time low-power execution of convolutional neural networks at the edge," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2018, vol. 10973 LNCS, pp. 49–64.
- [18] A. Hekler *et al.*, "Superior skin cancer classification by the combination of human and artificial intelligence," *Eur. J. Cancer*, vol. 120, pp. 114–121, Oct. 2019.
- [19] R. C. Maron *et al.*, "Systematic outperformance of 112 dermatologists in multiclass skin cancer image classification by convolutional neural networks," *Eur. J. Cancer*, vol. 119, pp. 57–65, Sep. 2019.
- [20] V. Pomponiu, H. Nejati, and N. M. Cheung, "Deepmole: Deep neural networks for skin mole lesion classification," in *Proceedings - International Conference on Image Processing, ICIP*, 2016, vol. 2016-August, pp. 2623–2627.

References

- [21] A. Romero Lopez, X. Giro-I-Nieto, J. Burdick, and O. Marques, "Skin lesion classification from dermoscopic images using deep learning techniques," in *Proceedings of the 13th IASTED International Conference on Biomedical Engineering, BioMed 2017*, 2017, pp. 49–54.
- [22] D. Gutman *et al.*, "Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016, hosted by the International Skin Imaging Collaboration (ISIC)," May 2016.
- [23] M. A. Marchetti *et al.*, "Results of the 2016 International Skin Imaging Collaboration International Symposium on Biomedical Imaging challenge: Comparison of the accuracy of computer algorithms to dermatologists for the diagnosis of melanoma from dermoscopic images," in *Journal of the American Academy of Dermatology*, 2018, vol. 78, no. 2, pp. 270-277.e1.
- [24] S. Han, J. Pool, J. Tran, and W. Dally, "Learning both weights and connections for efficient neural network," in *Advances in neural information processing systems*, 2015, pp. 1135–1143.
- [25] E. Guerra-Rosas and J. Álvarez-Borrego, "Methodology for diagnosing of skin cancer on images of dermatologic spots by spectral analysis," *Biomed. Opt. Express*, vol. 6, no. 10, p. 3876, Oct. 2015.
- [26] M. A. Al-masni, D. H. Kim, and T. S. Kim, "Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification," *Comput. Methods Programs Biomed.*, vol. 190, p. 105351, Jul. 2020.
- [27] K. M. Hosny, M. A. Kassem, and M. M. Foaud, "Classification of skin lesions using transfer learning and augmentation with Alex-net," *PLoS One*, vol. 14, no. 5, p. e0217293, May 2019.
- [28] A. Aljawawdeh, E. Imraiziq, and A. Aljawawdeh, "Enhanced k-mean using evolutionary algorithms for melanoma detection and segmentation in skin images," *Int. J. Adv. Comput. Sci. Appl.*, vol. 8, no. 12, pp. 477–483, 2017.
- [29] V. M. M, "Melanoma Skin Cancer Detection using Image Processing and Machine Learning," *Int. J. Trend Sci. Res. Dev.*, vol. Volume-3, no. Issue-4, pp. 780–784, Jun. 2019.
- [30] S. Wager, S. Wang, and P. S. Liang, "Dropout training as adaptive regularization," in *Advances in neural information processing systems*, 2013, pp. 351–359.

Thank You