Enhanced Melanoma Classifier with VGG16-CNN
Mary Adewunmi
National Center for Technology Management (NACETEM)
Lagos, Nigeria.
Mary.adewunmi@nacetem.org.ng, madewunmi23@gmail.com

Introduction
Melanoma has arisen as a major public health challenge in recent decades (Schadenfeld et al., 2015). Melanoma is the most severe kind of skin cancer, yet it can be treated if detected early. Melanoma develops when melanocytes, the pigment-producing cells present in the skin, eye, inner ear, and leptomeninges, develop genetic abnormalities (Domingues et al., 2018). Despite accounting for only around 1% of all skin malignant tumors, cutaneous melanoma is the most aggressive and deadly type of skin cancer. The rising incidence rates and mortality rates of melanoma have prompted a renewed focus on early identification and prevention. Dermoscopy greatly enhances the diagnostic accuracy of the naked eye examination, according to several meta-analyses. However, dermatologists and medical practitioners who were professionally trained in various dermoscopic algorithms had an average sensitivity of about 80% for identifying melanoma.

Artificial intelligence has recently been shown to be capable of categorizing images of benign nevi and melanoma with dermatologist-level precision, according to recent articles. Higher model performance correlates with a large number of images, however, it is not always cost-effective to run a large number of image datasets with a deep learning network. It is pertinent for us to see ways to cushion this trend in the number of training images and the cost of training the model used.

Convoluted neural networks (CNNs) have been utilized in recent research in digital skin diagnostics to categorize melanoma images with accuracies comparable to those attained by dermatologists (Nasr-Esfahani et al., 2016; Perez et al., 2019). Prior studies used a huge number of images to train their algorithms, which were then confirmed by consensus decisions. When photos are validated in this way, there is a strong chance that the CNN will learn the dermatologists’ decision-making process, including all probable errors. The rising incidence rates and mortality rates of melanoma have prompted a renewed focus on early identification and prevention. This work focuses on Melanoma amongst 9 classes of Skin cancer (see Fig. 1).

Methods
Datasets
The Dataset is provided by SIIM ISIC (Rotemberg et al., 2021). The dataset was made available for download as part of a live competition on the Kaggle platform from May 27, 2020 through August 20, 2020. It’s licensed under the Creative Commons Attribution-Non Commercial 4.0 International (CC BY-NC 4.0) license and can be found at https://doi.org/10.34970/2020-d01. This comprises of 2297 Image datasets belong to 9 classes of Images lesions: which are 'acanthotic keratosi', 'basal cell carcinoma', 'dermatofibroma', 'melanoma', 'nevus', 'pigmented benign keratosis', 'seborheic keratosis', 'squamous cell carcinoma', 'vascular lesion'.

Implementation
We used an approach similar to (Mamiya & Miyata, 2020) in which authors first preprocess images with vgg16 and used it to denoise the input images and generate unlabeled images that was trained with CNN. Our hyper parameter configurations are the following:

- Image preprocessing: Image data generator (Chollet, 2016)
- Learning rate: 0.0001
- Pooling: max pooling with stride 2
- Loss: Binary cross entropy
- Optimizer: Adam
- Training Model: Sequential Conv2D
- Epochs: 10
- Verbose: 2
- Metrics: Area under curve (AUC) (Bradley, 1997)

Results
In this work, we have studied:

- Preprocessing images with VGG16
- Training images with CNN
- Classification of lesion images into Melanoma and Non melanoma (see figure 5). The results were classified correctly when matched up with the ground truth.

Conclusion
We have developed a Melanoma Classifier, which achieved a performance accuracy of 93%, precision of 1 and recall of 0.5% with Melanoma images, through preprocessing images with VGG16. Overall, this indicated that training images need to be preprocessed before they can be trained on deep learning models especially when aiming at higher performance accuracy.

Future Recommendation
The test datasets for Melanoma was very few compared to the other classes of skin cancer lesion images, which affected the recall and the F1 score of the predicted test images.

GitHub

References
Bradley, A. P. (1997). The use of the area under the ROC curve in the evaluation of machine learning algorithms. Pattern Recognition, 30(7), 1145-1159.
Chollet, F. (2016). Building powerful image classification models using very little data. Keras Blog, 5.
Domingues, B., Lopes, J. M., Soares, P., & Pópulo, H. (2018). Melanoma treatment in review. ImmunoTargets and Therapy, 7, 35-49. https://doi.org/10.2147/ITT.S134842
Mamiya, K., & Miyata, T. (2020). Few-Class Learning For Image-classification-Aware Denoising. 2020 IEEE International Conference on Image Processing (ICIP). 946-952.
Mendonca, T., Ferreira, P. M., Marques, J. S., Marcal, A. R. S., & Rozeira, J. (2013). PH 2-A dermoscopic image database for research and benchmarking. 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBB), 5437-5440.
Nasr-Esfahani, E., Samavi, S., Karimi, N., Soroushmehr, S. M. R., Jafari, M. H., Ward, K., & Najarian, K. (2016). Melanoma detection by analysis of clinical images using convoluted neural network. 2016 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBB), 1373-1376.
Perez, F., Avila, S., & Valle, E. (2019). Solo or ensemble? choosing a cnn architecture for melanoma classification. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 0.
Rotemberg, V., Kurtzany, N., Beta-Stablein, B., Caffery, L., Chousakos, E., Codella, N., Combalia, M., Duzio, S., Gutera, P., & Gutman, D. (2021). A patient-centric dataset of images and metadata for identifying melanomas using clinical context. Scientific Data, 8(1), 1–8.
Schadendorf, D., Fisher, D. E., Garbe, C., Gershenwald, J. E., Grob, J.-J., Halpern, A., Herlyn, M., Marchetti, M. A., McArthur, G., Ribas, A., Roesch, A., & Hauschild, A. (2015). Melanoma. Nature Reviews Disease Primers, 1(1), 15003. https://doi.org/10.1038/nrdp.2015.3

Figure 1: Illustration of (a) Benign lesions, (b) Melanoma lesions (Mendonça et al., 2013)

Figure 2: Classes of images from the train set by ISIC

Figure 3: Architecture of the VGG16-CNN Model

Figure 4a: AUC showing Training and validation Accuracy

Figure 4b: AUC showing Training and validation Loss

Figure 5: Classification results into Melanoma and Not Melanoma