ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 8| Issue: 8| August 2022|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2022: 8.205 || ISI Value: 1.188

SKIN CANCER CLASSIFICATION

Shiva Shashank Dhavala[1], Nagaraj Shrikrishna Hegde[2], Srihari C[3]
[1,2,3]*R V College of Engineering Mysore Rd, RV Vidyaniketan Post, Bengaluru, Karnataka, 560059*

ABSTRACT

Skin cancer is considered as one of the most dangerous types of cancers and there is a drastic increase in the rate of deaths due to lack of knowledge on the symptoms and their prevention. Thus, early detection at a premature stage is necessary so that one can prevent the spreading of cancer. Skin cancer is further divided into various types out of which the most hazardous ones are Melanoma, Basal cell carcinoma and Squamous cell carcinoma. The project is about detection and classification of various types of skin cancer using machine learning and image processing tools. In the pre-processing stage, dermoscopic images are considered as input. Dull razor method is used to remove all the unwanted hair particles on the skin lesion, then Gaussian filter is used for image smoothing. For noise filtering and to preserve the edges of the lesion, Median filter is used. Color is an important feature in analyzing the type of cancer, color-based k-means clustering is performed in segmentation phase. The statistical and texture feature extraction is implemented using Asymmetry, Border, Color, Diameter, (ABCD) and Gray Level Co- occurrence Matrix (GLCM).

KEYWORDS: ***Melanoma, Deep Learning, image segmentation***

1. INTRODUCTION

The aim of this project is to develop a deep learning based model driven architecture to classify dermal cell images. Skin cancer rates are the 6th most types of cancer that are increasing globally. Generally, skin consists of cells and these cells comprise tissues. Thus, cancer is caused due to the abnormal or uncontrolled growth of the cells in the corresponding tissues or to the other adjacent tissues. Exposure to UV rays, depressed immune system, family history, etc., the reason for the occurrence of cancer. This type of irregular pattern of cell growth can be given as either benign or malignant. Benign tumors are can- cer type and generally, they are considered as moles, which are not harmful. Whereas, malignant tumors are treated as cancer which is life threatening. They can also damage the other tissues of the body. The layer of the skin consists of three types of cells: Basal cell, Squamous cell, and Melanocyte. These are responsible for the tissues to become cancerous. There are different types of skin cancers, of which Melanoma, Basal cell carcinoma (BCC), Squamous cell carcinoma (SCC), which are considered as dangerous types. Early detection of melanoma at its premature stage is the best way to decrease the effect of the disease.

2. LITERATURE REVIEW

Authors Alkhushayni, S.et al. in [1] carried out a critical assessment of existing machine learning and deep learning models for the classification of skin tumors. The work concluded the performance of DenseNet201>CNN> SVM. Authors Created 3 custom CNN models with additional layers. All 3 custom CNNs outperformed traditional methods.

Authors S. Bechelli et al. in [2] carried out a critical assessment of machine learning and deep learning models for the classification of skin tumors. The authors performed segmentation and preprocessing steps to obtain gray level skin level images with pre-trained Levenberg Marquardt Neural Network for clustering and classification from PH2 database.

Authors H. Alquran et al. in [3] tried classification of cancer using Principal Component Analysis(PCA). Authors implemented statistical feature extraction using GLCM(Gray level co-occurrence matrix).The features based on GLCM and gray level histogram allow the differentiation of homogeneous and high contrast or luminous tissue areas.

Authors of [4] T. Brinker et al. performed systematic review of the state-of-the-art research on classifying skin lesions with CNNs. The authors concluded that CNN with transfer learning is much more efficient than traditional CNN.

Authors in [5]. E. Jana et al., studied skin lesions based on dermoscopic images PH2 datasets (200 images) using 4 different machine learning methods namely; ANN, SVM, KNN and Decision Tree. Correctly classified instances were found as 92.50%, 89.50%, 82.00% and 90.00% for ANN, SVM, KNN and DT respectively.

Authors in [6]Pacheco, A et al., diagnose melanoma and non-melanoma using a dermoscopic image. They also diagnose benign and malignant cutaneous tumors among 12 types of skin diseases using clinical images.

3. DETAILS

The dataset used in the paper is openly available on Kaggle (SIIM-ISIC Melanoma Classification, 2020). It consists of around forty-four thousand images from the same patient sampled over different weeks and stages. The dataset consists of images in various file formats. The raw images are in DICOM (Digital Imaging and COmmunications in Medicine), containing patient metadata and skin lesion images. DICOM is a commonly used file format in medical imaging. Additionally, the dataset also includes images in TFRECORDS (TensorFlow Records) and JPEG format.

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 8| Issue: 8| August 2022|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2022: 8.205 || ISI Value: 1.188

4. METHODOLOGY

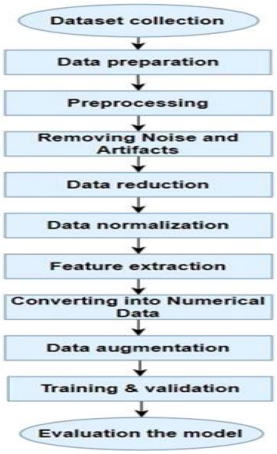


Fig. 1. Methodology Flowchart

4.1. Data Preprocessing

In any machine learning project, it is critical to set up a trustworthy validation scheme, in order to properly evaluate and compare models. This is especially true if the dataset is small to medium size, or the evaluation metric is unstable, which is the case of this project. There are 33k images in train data. However, only 1.76% are positive samples (i.e., malignant). The small number of positives causes the AUC metric to be very unstable, even with 5-fold cross validation.

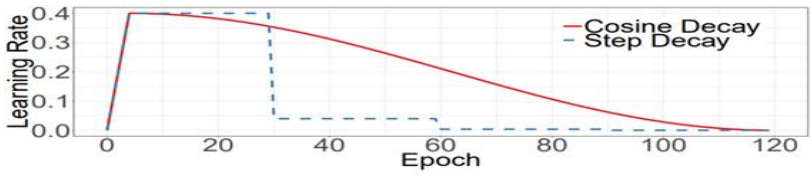
4.2. Data Augmentation

In a small size dataset, image augmentation is required to avoid overfitting the training dataset. After data aggregation, we have around 46k images in the training set. The dataset contains significant class imbalance, with most of the classes having an "Unknown" category. We have defined our augmentation pipeline to deal with the class imbalance. The augmentation that helps to improve the prediction accuracy of the model is selected.

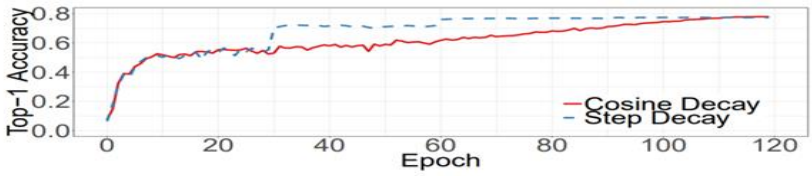
5. RESULTS

We have used ensemble terminology to train diverse models and take the average probability ranks of the models to get the final prediction. The model configuration is as follows:

1. Backbone Pre-trained CNN Model: Efficient Net B4, B5 and B7. We have chosen to use the B4, B5 and B7 variant of the efficient net over B0 as they have achieved higher accuracy on ImageNet competition.
2. Targets: All the models are trained in nine categories.
3. Original images are cropped to 68x768 and 512x512 pixels. To reduce the random noise and black border on the edge of the images.
4. Resized image input sizes to 380x380 and 448x448 pixels. The images are resized to lower resolution due to GPU memory constraints. Otherwise, it was planned to load the images with the original cropped image pixels.
5. Cosine Decay learning rate is set to 3e-5 and 1e-5 with 1 Warmup epoch. Along with the pre-trained model, we are using Cosine decay with a warmup learning rate scheduler. Warmup strategy gradually increases the learning rate from zero to the initial learning rate during initial Nth epochs or m batches. Cosine decay is used in conjunction with the warmup learning rate scheduler to decrease the initial learning rate value steadily. Cosine decay is used rather than exponential or step decay. It reduces the learning rate slowly at the start and end while falling linearly in the middle—cosine decay helps to improve the training process.



(a) Learning Rate Schedule



(b) Validation Accuracy

Fig. 2. Network Configuration

6. Optimiser: Adam. Adam combined the best properties of RMSProp and AdaGrad to handle the sparse gradients on the noisy problems. As we have sparse data, Adam is used because of the adaptive learning rate.

7. Training Epoch: 15. As we are using the ensemble methodology, we have trained all the variants of the EfficientNet model on 15 epoch.

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 8| Issue: 8| August 2022|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2022: 8.205 || ISI Value: 1.188

8. Training and validation batch size of 8 for B4 and 4 for B5 and B7 is used. The reason behind choosing the small batch size is due to GPU memory constraints. Otherwise, we have planned to use a batch size of 64 for the training and validation set.

6.CONCLUSION

One of the deadliest cancer forms is melanoma, and the proportion of people getting affected by melanoma is increasing rapidly. To make the solution available to the public and dermatologists, we have successfully integrated the optimized model with our CAD system.

The model is trained on a constant split; that is, the training and testing split remains the same in every model. But to ensure the splits are relatively unbiased, K-fold Cross-Validation can be used. A model can become robust if trained on a five-fold split. So, a single fold contains 15 epoch, and by the end of the training process, the model will be trained on five different holdouts set with 75 epoch in total (5 fold x 15 Epoch). K-fold Cross-Validation strategy only works if a more significant number of GPUs are available as the EfficientNet model takes longer to train.

Also, the project can be extended by detecting the skin cancer region with bounding boxes and providing the proportion of cancerous cells in the proposed region. It will help dermatologists understand where the network is looking, and it also helps improve the network performance if the wrong inference is performed.

REFERENCES

1. *Alkhushayni, S., Al-zaleq, D., Andradi, L. and Flynn, P., 2022. The Application of Differing Machine Learning Algorithms and Their Related Performance in Detecting Skin Cancers and Melanomas. Journal of Skin Cancer, 2022, pp.1-11.*
2. *S. Bechelli and J. Delhommelle, "Machine Learning and Deep Learning Algorithms for Skin Cancer Classification from Dermoscopic Images", Bioengineering, vol. 9, no. 3, p. 97, 2022. Available: 10.3390/bioengineering9030097 [Accessed 13 May 2022].*
3. *H. Alquran et al., "The melanoma skin cancer detection and classification using support vector machine", 2017 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT), 2017. Available: 10.1109/aeect.2017.8257738 [Accessed 13 May 2022].*
4. *T. Brinker et al., "Skin Cancer Classification Using Convolutional Neural Networks: Systematic Review", Journal of Medical Internet Research, vol. 20, no. 10, p. e11936, 2018. Available: 10.2196/11936 [Accessed 13 May 2022].*
5. *E. Jana, R. Subban and S. Saraswathi, "Research on Skin Cancer Cell Detection Using Image Processing," 2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 2017, pp. 1-8, doi: 10.1109/ICCIC.2017.8524554.*
6. *Pacheco, A. and Krohling, R., 2022. Recent advances in deep learning applied to skin cancer detection. [online] arXiv.org. Available at: <https://doi.org/10.48550/arXiv.1912.03280> [Accessed 27 July 2022].*