IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SKIN MELANOMA DETECTION USING NEURAL NETWORK

V.Rajalakshmi [1] , Mrs.P.Jasmine Lois Ebenazer [2]

Department of Computer Applications, Sarah Tucker College, Thirunelveli-7.

Abstract: A skin lesion is a part of the skin which has an uncommon growth or appearance in comparison with the skin around it. While most are harmless, some can be warnings of skin cancer. Melanoma is the deadliest form of skin cancer and its early detection in thermoscopic images is crucial and results in increase in the survival rate. The clinical (asymmetry, border irregularity, color variation and diameter greater than 6mm) rule is one of the most widely used method for early melanoma recognition. However, accurate classification of melanoma is still extremely difficult due to following reasons(not limited to): great visual resemblance between melanoma and non-melanoma skin lesions, less contrast difference between skin and the lesions etc. There is an ever-growing need of correct and reliable detection of skin cancers. Advances in the field of deep learning deems it perfect for the task of automatic detection and is very useful to pathologists as they aid them in terms of efficiency and accuracy. In this thesis various state of the art deep learning frameworks are used. An analysis of their parameters is done, innovative techniques are implemented to address the challenges faced in the tasks, segmentation, and classification in skin lesions. • Segmentation is task of dividing out regions of interest. This is used to only keep the ROI and separate it from its background.• Classification is the task of assigning the image a class, i.e., Melanoma(Cancer) and Nevus(Not Cancer). A pre-trained model is used and fine-tuned as per the needs of the given problem statement/dataset. Experimental results show promise as the implemented techniques reduce the false negatives rate, i.e., neural network is less likely to misclassify a melanoma.

***Index Terms* – Neural Networks, Skin Melanoma Detection**

I. INTRODUCTION

Melanoma is the most dangerous form of skin cancer and has the ability to spread to different parts of the body is left untreated. It results in approximately 75% of deaths related to skin cancer. Therefore, it is crucial to correctly detect it at a much earlier stage, this results in a higher survival rate of patients. Clinical diagnosis of melanoma with an unaided eye is only about 60%. Extensive research and advancements have been made in the field of deep learning in computer vision and they have been gaining a lot of dominance. Today, it can outperform humans in multiple areas such as detection, classification in digital images with less than 5%. An atomic system that can be relied upon for melanoma detection is valuable for the pathologists as it increases their effectiveness and accuracy. These can be readily run on easily available hardware, hence increasing their reach. Dermoscopy technique is a noninvasive technique in which magnified and clear images of cancer suspected skin regions are taken. This helps in enhancing the visual features of the skin lesion and aids in detection. Nonetheless, the task of detecting melanoma using deep learning techniques poses several challenges. Few reasons are(not limited to): Subtle visual differences between melanoma and non-melanoma patches, less contrast difference between skin and lesions also, variations in the skin conditions, e.g., color of the skin, hair present around the patch. This results in the melanoma patch having different type of characteristics, color, etc.

Segmentation is a fundamental step towards classification in a lot of approaches. A comprehensive algorithms study on automated skin lesion segmentation is available in. Segmentation can help increase the accuracy of classification. A lot of studies have been done to achieve decent segmentation results. On the basis of results obtained from segmentation, features can hence be extracted for melanoma detection.

Even though a lot of work has been carried out, there is still a lot of place for performance improvement in segmentation and classification of skin lesions. The International Skin Imaging Collaboration Melanoma Project is a focused towards facilitating the application of digital skin imaging to reduce mortality due to melanoma. They have developed and are expanding their data-set archive of skin images since 2016. It is an open-source public access archive to facilitate the development and testing of automated diagnostic systems. They have set new standards in the area of dermoscopic feature extraction.

II. LITERATURE SURVEY

In[1] In this paper, a method for skin lesion classification and segmentation as benign or malignant is proposed using image processing and machine learning. A novel method of contrast stretching of dermoscopic images based on the methods of mean values and standard deviation of pixels is proposed. Then the OTSU thresholding algorithm is applied for image segmentation. After the segmentation, features including Gray level Co-occurrence Matrix (GLCM) features for texture identification, the histogram of oriented gradients (HOG) object, and color identification features are extracted from the segmented images. Principal component analysis (PCA) reduction of HOG features is performed for dimensionality reduction. Synthetic minority oversampling technique (SMOTE) sampling is performed to deal with the class imbalance problem. The feature vector is then standardized and scaled. A novel approach of feature selection based on the wrapper method is proposed before classification. Classifiers including Quadratic Discriminant, SVM (Medium Gaussian), and Random Forest are used for classification. The proposed approach is verified on the publicly accessible dataset of ISIC-ISBI 2016. Maximum accuracy is achieved using the Random Forest classifier. The classification accuracy of the proposed system with the Random Forest classifier on ISIC-ISBI 2016 is 93.89%. The proposed approach of contrast stretching before the segmentation gives satisfactory results of segmentation. Further, the proposed wrapper-based approach of feature selection in combination with the Random Forest classifier gives promising results as compared to other commonly used classifiers.

In[2] Skin Cancer is one of the hazardous types of cancer. It is basically an unusual growing of skin cells which mostly develops on skin contact with the sun. Nowadays it also develops on areas of the skin which is not in contact to sunlight. It is essential to detect cancer at prior or else it tends to gradually spread over the other parts of the body. Here we present numerous machine learning techniques that are used to identify various types of cancer and classify whether it is Malignant or Benign. There are four main steps included in the process namely Preprocessing, Segmentation, Feature Extraction and Classification. The Paper concentrates on the comparison of different types of methods which can be used for the above steps.

In[3] Skin cancer is the far most common type of cancer. This can be treated effectivelyif it found early. The cancer detection in early stages is very expensive. Skin cancer is theabnormal growth of the skin cells. These are highly curable when identified and treated early. There are four types of skin cancers: Actinic Keratoses (AK), Basal cell carcinoma (BCC), Dermatofibroma and Melanoma. The late identification of cancer leads to the spread over other organs. The skin cancer can be detected from the images using convolution neural networks. ISIC image dataset and HAM10000 dataset will be used in this implementation. Transfer learning improves the performance of the model in CNN's.Pre trained models are used to extract features, which further used to classify types of skin cancer. The machine learning and deep learning methods used in this implementation are Random Forest, SVM, CNN and Dense net.

In[4] Skin Cancer is a dangerous disease which occurs in almost all age groups especially at an older age. It is due to the abnormal growth or rapid growth in the epidermal layer of the skin, which leads to the growth of tumor. Cancer need to be differentiated from other skin diseases as it occurs on in tissue levels where as other diseases affects to only upper layer of epidemics. As the treatment and detection is at high cost, technology can help predict the cancer at early stage, thereby reducing the detection of cancer's cost athletes and also can help save time. A fully accurate machine to detect cancer stages is difficult to prepare but at least a probability can be given and thus the medical test can further be performed if the accuracy of the machine is not up to mark. So we have proposed a CNN(Convolutional Neural Network) which can predict and classify skin cancer with a better accuracy as compared to normal Support Vector Machine.

In[5] The proposed algorithm applies feature extraction using ABCD rule, GLCM and HOG feature extraction for early detection of skin lesion. In the proposed work, Pre-processing is to improve the skin lesion quality and clarity to reduce artifacts, skin color, hair, etc., Segmentation was performed using Geodesic Active Contour (GAC) which segments the lesion part separately which was further useful for feature extraction. ABCD scoring method was used for extracting features of symmetry, border, color and diameter. HOG and GLCM was used for extracting textural features. The extracted features are directly passed to classifiers to classify skin lesion between benign and melanoma using different machine learning techniques such as SVM, KNN and Naïve Bayes classifier. In this project skin lesion images were downloaded from International Skin Imaging

Collaboration (ISIC) in which 328 images of benign and 672 images of melanoma. The classification result obtained is 97.8 % of Accuracy and 0.94 Area under Curve using SVM classifiers. And additionally the Sensitivity obtained was 86.2 % and Specificity obtained was 85 % using KNN.

III. METHODOLOGY

Image Segmentation is one of the key topics in the field of image processing and computer vision and plays a crucial role in applications areas such as medical image analysis, perception in robots, augmented reality, image compression and much more.

Segmentation involves dividing a visual input into segments in order to simplify its analysis. From all the different regions/objects that the networks segment we pick only theimportant ones for our analysis. The image is a collection of different pixels, we group together pixels which belong to the same category/class. It is generally done using a bounding-box method where we place a box around the region of interest or a pixel wise labelling resulting in different classes being highlighted with different colors.

Our goal using a segmentation algorithm is to extract the region of a mole from a given image and remove the background which is the skin. We are using the ISIC-2018 data setfor the task of segmentation and it contains 2594 images and masks.

Mask is the ground truth of the input image, meaning it contains pixel level information of which pixel has a class mole and not a mole. In terms of numerical values, the mask is a binary one, which means it contains 0 and 1 as pixel values. 0 corresponds tothat pixel not being a mole and 1 meaning it is a mole. It is a gray scale image with a blackand white appearance and contains only a single channel. An example of an image and itsmask is given in the figure 2.1.

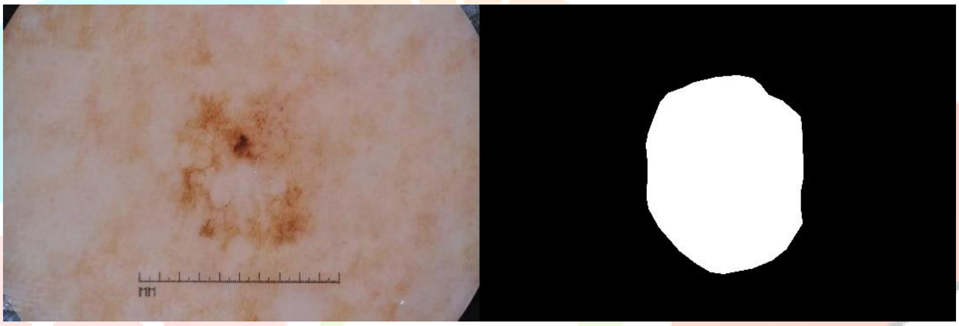

Figure 2.1: Image and Mask

Pre-Processing

The input images for training the deep learning model were normalized before the training process. This helps in getting it within a certain threshold range, it reduces the skewness[15] which helps the network learn better and faster. Mean pixel value and standard deviation of the three-color channels namely, Red-Green-Blue was estimated. Using the below values data was normalized and equation 2.1 was used for normalization.

- Mean r-g-b value: (0.708, 0.582, 0.536)

- Standard deviation: (0.0978, 0.113, 0.127)

$$Output[Channel] = \frac{Input[Channel] - Mean[Channel]}{Standard\ Deviation[Channel]}$$

An example of original image and normalized image can be found in Figure 2.2.

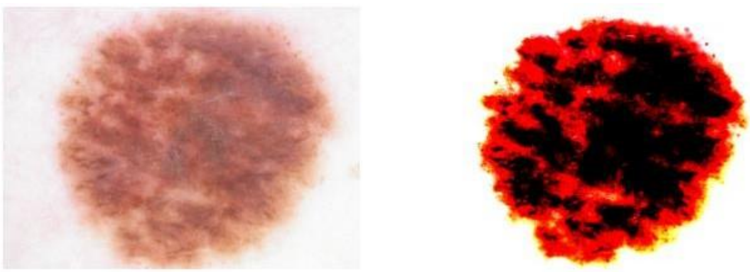

Figure 2.2: Original Image and Normalized Image

Data-Augmentation & Dice Index

Data augmentation is a set of techniques used to increase the amount of data available by adding moderately modified duplicate of data or create synthetic data newly from the already existing data. This helps to reduce overfitting[16] when training the model by acting as a regularizer[17]. There are a plethora of data augmentation techniques and were randomized with a probability of 50% of any of them happening. The performed techniquesand visual examples are discussed in this section.

- Horizontal flipping: Horizontal flip augmentation is when the columns of the inputimage is reversed.

Figure 2.3: Original Image and Flipped Image

- Rotation: Rotation augmentation is done by rotating the image between -180º and 180º.

Figure 2.4: Original Image and Rotated Image

- Resized crop: Resized crop augmentation is when a random subset is created from theoriginal image and scaled back to a given size.

- All images are all resized to 400x400 for training purpose. All the previous techniquescombined generate an image the same as in figure 2.6.

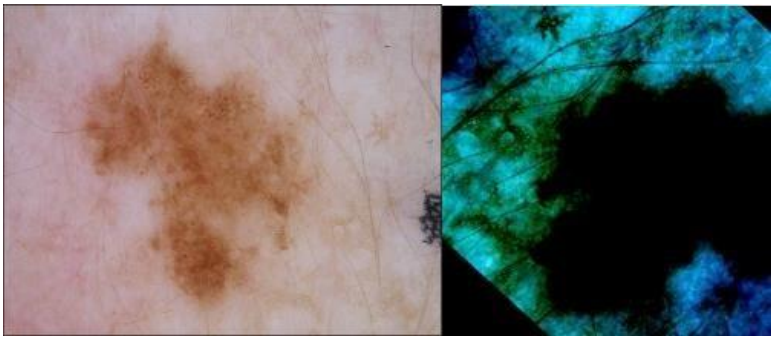

Figure 2.5: Original Image and Transformed Image

The same spatial data augmentation is applied to the mask as well. It keeps the image and mask both identical in terms of orientation. If both were to be aligned differently for training, the model would not learn anything useful from it and prediction would be nearrandom. Dice index is a statistical tool to find the similarity between two images andwas used as the metric for accuracy.

IV. CONCLISION

In this thesis, it has summarized the work for melanoma classification so far. We have reviewed that DL has numerous potential applications in the dermatologist's workflow from diagnosis to treatment. DL can improve the dermatologist's practice from diagnosis to personalized medicine. Recent advancements in access to large datasets (e.g., electronic medical records, image databases, omics), faster computing, and cheaper data storage have encouraged DL algorithms' development with human-like intelligence in dermatology. There are many promising opportunities for DL in the dermatologist's practice. The classification of images through CNNs has garnered the most attention for its potential to increase the accessibility of skin cancer screenings and streamline the workflow of dermatologists.

Further research in DL should be transparent by making algorithms anddatasets available to the public for additional validation and testing. Beforecoming to market, rigorous peer-reviewed prospective clinical trials shouldbe conducted. Overall, involving more dermatologists in developing andtesting DL is imperative for creating functional and clinically relevant technology.

Mobile devices, such as smartphones, PDAs, and tablets, become anessential part of human life. Embedding AI diagnosis and skin diseasetreatment on intelligent machines will be a significant trend in the future.However, most skin diseases are diagnosed based on high-performancegraphics processors. The algorithm's computational complexity should beminimized while improving the algorithm recognition capability to ensurethat it can be easily used on mobile phones and wearable intelligent devices.This study is of great significance for AI diagnosis and treatment of skindiseases.

Although lesion segmentation, feature segmentation, feature generation,and classification are the significant steps, proper attention should be given to the additional steps, which in most cases are the major contributors to asuperior outcome.

REFERENCES

1.Javaid, M. Sadiq and F. Akram, "Skin Cancer Classification Using Image Processing and Machine Learning," *2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST)*, 2021, pp. 439-444, doi: 10.1109/IBCAST51254.2021.9393198.

2.R. Desai, J. Panchal, A. Mitra, S. Mamlekar, H. Chari and S. Aswale, "Skin Cancer Detection Using Machine Learning: A Survey," 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM), 2022, pp. 31-35, doi: 10.1109/ICIEM54221.2022.9853084.

3.M. Ramachandro, T. Daniya and B. Saritha, "Skin Cancer Detection Using Machine Learning Algorithms," 2021 Innovations in Power and Advanced Computing Technologies (i-PACT), 2021, pp. 1-7, doi: 10.1109/i-PACT52855.2021.9696874.

4.S. Labde and N. Vanjari, "Prediction of Skin Cancer Using CNN," 2022 3rd International Conference for Emerging Technology (INCET), 2022, pp. 1-4, doi: 10.1109/INCET54531.2022.9825093.

5.M. Vidya and M. V. Karki, "Skin Cancer Detection using Machine Learning Techniques," 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), 2020, pp. 1-5, doi: 10.1109/CONECCT50063.2020.9198489.

6.P. Singh, M. Kumar and A. Bhatia, "A Comparative Analysis of Deep Learning Algorithms for Skin Cancer Detection," 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 2022, pp. 1160-1166, doi: 10.1109/ICICCS53718.2022.9788197.

7.A. -R. H. Ali, J. Li and G. Yang, "Automating the ABCD Rule for Melanoma Detection: A Survey," in IEEE Access, vol. 8, pp. 83333-83346, 2020, doi: 10.1109/ACCESS.2020.2991034.

8.T. Guergueb and M. A. Akhloufi, "Multi-Scale Deep Ensemble Learning for Melanoma Skin Cancer Detection," 2022 IEEE 23rd International Conference on Information Reuse and Integration for Data Science (IRI), 2022, pp. 256-261, doi: 10.1109/IRI54793.2022.00063.

9.L. Gaur, U. Bhatia and S. Bakshi, "Cloud Driven Framework for Skin Cancer Detection using Deep CNN," 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM), 2022, pp. 460-464, doi: 10.1109/ICIPTM54933.2022.9754216.

10. L. D. Biasi, A. A. Citarella, M. Risi and G. Tortora, "A Cloud Approach for Melanoma Detection Based on Deep Learning Networks," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 3, pp. 962-972, March 2022, doi: 10.1109/JBHI.2021.3113609.