

Detection of Different Degrees of Skin Burn using YOLOv3

¹Shubham Baid, ²Shad Danish Akhtar, ³Sridevi Kashinath Alawandi, ⁴Kiran M

^{1,2,3,4}School of Computing and Information Technology
REVA University, Bengaluru, India

¹r17cs391@cit.reva.edu.in, ²r17cs369@cit.reva.edu.in, ³r17cs407@cit.reva.edu.in,
⁴kiranm@reva.edu.in

Article Info

Volume 83

Page Number: 4423-4426

Publication Issue:

May - June 2020

Abstract

A skin burn is an injury, cellular tissue damage and protein denaturation caused by heat, electricity, chemicals or sunlight. These skin burns are defined by the area they cover and how deep they are. The burn degree is determined by the number of skin layers affected. A large injury may have areas with different depths. In this paper we use convolutional neural network, YOLOv3 to detect different degrees of skin burn. Experimental result shows that our state-of-the-art model, YOLOv3 yielded an incremental accuracy of 86% which is trained on approximately 1400 images compared to SVM and MDS based models and the tested with 24 test images. Also, in webcam live capturing we obtained an average frame per second of 16.7 with NVIDIA 1050.

Keywords: Skin Burn; Degree of Burn; Convolutional Neural Network; YOLOv3

Article History

Article Received: 19 November 2019

Revised: 27 January 2020

Accepted: 24 February 2020

Publication: 12 May 2020

1. Introduction

Skin burns are commonly caused by steam or hot liquids, flammable liquids, and gases, building fires. A large burn injury is likely to include burned areas of different depths. Treatments for skin burns depends on the number of skin layers damaged. Burns affecting the upper layer of skin can be cured by simple pain medication while major ones may require professional care. Superficial burns can be healed by cooling with tap water. Burns often lead to infections that are treated using Tetanus toxoid.

TBSA (Total Body Surface Area) percentage is used to measure the size of the burn in partial and full thickness burns. Methods used to determine TBSA are Lund and Bowder chart, Wallace rule of nines and estimations based on palm size. The rule of nines is accurate for a person above 16 years of age. More efficient estimates are made using Lund and Bowder chart that consider the varying proportions of body parts in adults and children.

2. Literature Survey

The purpose of the research in the paper D. P. Yadav et al. [1] was to unfold a feature extraction model to classify the skin burns. The method used is SVM. The data used for training was obtained from the BIP US database. Training is carried by classifying images by

those that are non-graft and those that need graft. The 74 images of the data set were tested using the Support Vector Machine based method and it acquired an accuracy of 82.43% from the model.

In the paper, M. S. Badea et al. [3], authors have proposed a method for burn detection. They have applied the pixelwise method as per the properties of a whole path. The pixel method is sensitive to noise and also expensive. This classification failed to provide accurate results.

A. Degree 1

First degree burns are considered superficial and affect the epidermis. The burn is dry, red, and painful.



Figure 1: Degree 1 Burn.

B. Degree 2

Second degree burns affect deep up to the dermis. These burns can be classified as superficial partial thickness burns and as deep partial thickness burns. In superficial partial thickness burns cause damage to the layer which contains capillaries, lymph vessels and sensory neurons. The deep partial thickness burn penetrates and reaches the reticular layer. The burn is red with blisters. It can be wet and is more painful than a degree 1 burn.

For partial thickness burns, it is cleaned with soap and water before dressing while for full thickness burns, surgical treatment like skin grafting is done. The blisters resulting from the burn are drained or if small in size, are left to heal.



(a)



(b)

Figure 2: Degree 2 Burn (a) Superficial partial thickness burn; (b) Deep partial thickness burn.

C. Degree 3

Third degree burn affects the entire epidermis and dermis. The burn is grey or black or waxy white to leathery. There is no blanching.



Figure 3: Degree 3 Burn.

D. Convolutional Neural Networks (CNNs)

Convolutional neural network is a kind of neural network used for effective image recognition and classification. The image classifications in CNNs is done by classifying it under certain categories. In CNN, each image passes through various convolution layers with filters, pooling, FC layers and applies the soft max function to distinguish an object with probable values of 0 and 1.

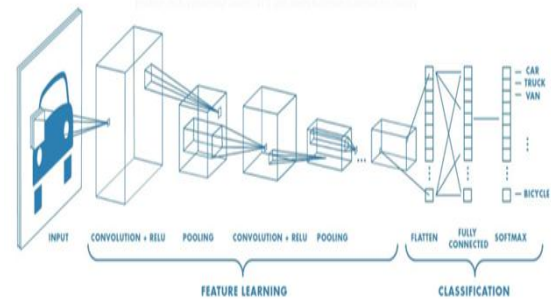


Figure 4: Neural Network with many Convolutional Layers.

E. Objectives

Our work focuses on detecting the degree of burn efficiently and accurately prior to treatment or tissue biopsy [4] [5].

3. Methodology

The skin burn images for our work were obtained by scrapping them from google images. These images need to go under manual sorting to filter out the irrelevant images. The images are labeled using the opensource tool, OpenLabeling. The images are labeled under 3 classes i.e. Degree 1, Degree 2 and Degree 3. The burn images are labeled under these classes as Degree 1 if the burn is dry and red. As Degree 2 if burn is red with blisters. As Degree 3 if the burn is waxy white, grey or black. For creating a detection model, YOLOv3 is used.

F. YOLOv3

YOLO works swiftly by looking at the image only once. It is an efficient object detection and classification algorithm. YOLO scans the entire image and hence produces accurate results.

The confidence scores of bounding boxes are calculated by YOLOv3 using logit regression. YOLOv3 uses various independent logistic classifiers instead of normalized exponential function for the prediction of the class confidence probabilities. This mechanism proves to be helpful when there are pooled objects in the image. DarkNet-53 is a feature extractor with 53 convolutional layers and residual blocks, this is being used by YOLOv3.[2]

Type	Filters	Size	Output
Convolutional	32	3 × 3	256 × 256
Convolutional	64	3 × 3 / 2	128 × 128
1x Convolutional	32	1 × 1	
1x Convolutional	64	3 × 3	128 × 128
1x Residual			64 × 64
2x Convolutional	128	3 × 3 / 2	
2x Convolutional	64	1 × 1	
2x Convolutional	128	3 × 3	64 × 64
2x Residual			32 × 32
8x Convolutional	256	3 × 3 / 2	
8x Convolutional	128	1 × 1	
8x Convolutional	256	3 × 3	16 × 16
8x Residual			8 × 8
8x Convolutional	512	3 × 3 / 2	
8x Convolutional	256	1 × 1	
8x Convolutional	512	3 × 3	16 × 16
8x Residual			8 × 8
4x Convolutional	1024	3 × 3 / 2	
4x Convolutional	512	1 × 1	
4x Convolutional	1024	3 × 3	8 × 8
4x Residual			
Avgpool		Global	
Connected		1000	
Softmax			

Figure 5: DarkNet-53 Model.

YOLOv3 also adds 53 more layers to the pre-existing layers of DarkNet-53, which combinedly makes it a convolutional architecture of 106 layers. It employs stride stepped convolution for down sampling instead of maximum pooling. It is made up of multiple convolutional layers along with base feature extractor layers, furthermore, enhancing its potential of multiscale prediction at three different sizes. As a result, detection of small objects from the image is accurately defined. The latest advancement in YOLOv3 is that the prediction layers have cross-layer connections. To make provision for efficient detection of small objects in the image, the feature maps obtained from the up-sampling operation were concatenated with the feature maps of the previous layers.

G. Implementation Blueprint

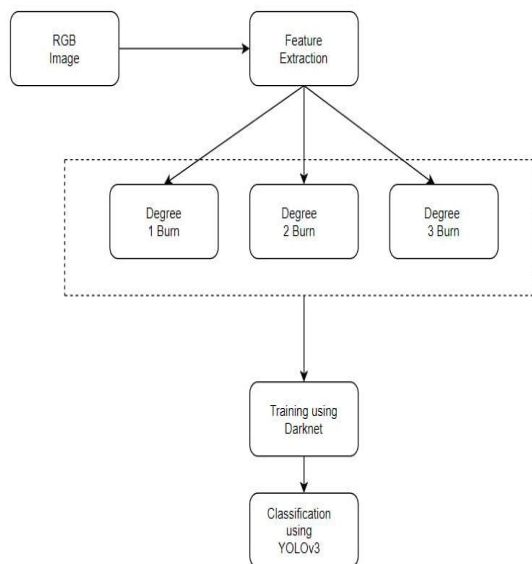


Figure 6: Block Diagram of Implementation.

4. Dataset

The image data needed for training the detection model was obtained using google image scraper. Obtained data underwent manual filtering for removal of irrelevant images.

Table 1: Burn Images Dataset

Sl. No.	Image Dataset of Skin Burn	
	Class Name	Total No.
1	Degree 1	577
2	Degree 2	452
3	Degree 3	441

5. Experimental Results

The figures 7, 8 and 9 present the detections made about the degree of burn. The test was conducted with 24 test images and an accuracy rate of 86% was obtained. In webcam live capturing we obtained an average frame per second of 16.7 with NVIDIA 1050.



Figure 7: Detection of Degree 2 Skin Burn.



Figure 8: Detection of Degree 3 Skin Burn.



Figure 9: Detection of Degree 3 Skin Burn.

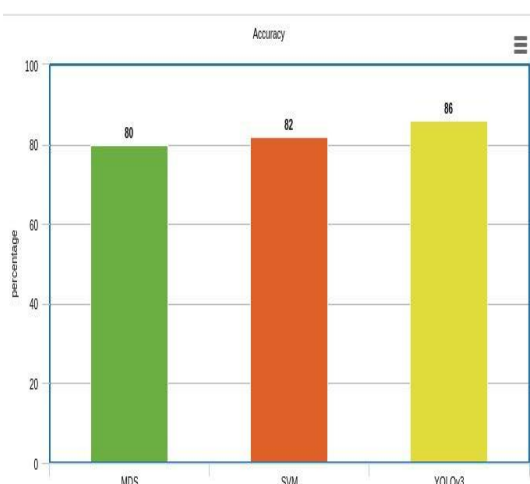


Figure 10: The graph shows the accuracy of three different models.

6. Conclusion and Future Enhancement

In the paper, D. P. Yadav et al. [1], the experimental results have shown that SVM based model yielded an accuracy of 82.43% which is comparatively better than MDS accuracy of 79.73%. Our state-of-the-art model, YOLOv3 yielded an incremental accuracy of 86% which is trained on approximately 1400 images. Earlier models detected the burns based on whether they need grafting or not, our YOLOv3 model detects the skin burn on three different degrees.

The future implementation and extension of this state-of-the-art model can go step further with better accuracy of the model with extra data to train, optimizing the model to easily integrate with smartphone applications, also by having better FPS with optimization of the model and ability to detect burns with heat maps as well.

References

- [1] D. P. Yadav, Ashish Sharma, Madhusudan Singh and Ayush Goyal, "Feature Extraction Based Machine Learning for Human Burn Diagnosis from Burn Images", IEEE Journal of Translational Engineering in Health and Medicine, article no. 1800507, July 2019.
- [2] Joseph Redmon, Ali Farhadi, "Yolov3: An Incremental Improvement", arXiv Journal, article no. 1804.02767, April 2018.
- [3] M. S. Badea, C. Vertan, C. Florea, L. Florea, and S. Badoiu, "Automatic burn area identification in color images," in Proc. Int. Conf. Commun. (COMM), 2016, pp. 65–68.
- [4] M. Pirtiniçetingül and C. Herman, "A heat transfer model of skin tissue for the detection of lesions: sensitivity analysis", Physics in Medicine and Biology, vol.55, October 2010, page 5933-5951.
- [5] WEI-PING ZHU and XIANG-RONG XIN, "Study on the Distribution Pattern of Skin Temperature in Normal Chinese and Detection of the Depth of Early Burn Wound by Infrared Thermography", Annals of the New York Academy of Sciences, vol. 888, issue 1 OCCUPATIONAL, July 2006, pp. 300-313.