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Deep Neural Nets in Real-Time Detection of Cancerous Epidermal Lesions

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***Abstract*— Skin cancer is among the most common malignancies amid humans. There are three basic types of skin cancers, i.e., basal-cell carcinoma, squamous cell carcinoma, and melanoma. Among the three basic types, melanoma has the lowest surviving rate however, basal-cell carcinoma is the most occurring cancer subtype. Therefore, early detection of skin cancer is necessary to increase the chance of survival of cancer patients. Since it has more prominent visual symptoms than other diseases, computer vision could be used to detect the advent of cancer early on. This study uses the YOLOv4 object detection algorithm to classify skin lesions into one of the three classes - basal cell carcinoma, squamous cell carcinoma, and melanoma. The training images are first manually annotated and then fed to the algorithm for object detection and classification. The results show that the YOLOv4 algorithm is not only accurate in detecting the skin cancer subtype but can also be integrated with dermoscopy IOT devices for real-time cancer detection by dermatologists.**

Keywords*— *skin cancer, basal cell carcinoma, squamous cell carcinoma, melanoma, object detection, YOLOv4, real-time disease detection

I. INTRODUCTION

Skin, covering 16% of total body mass, is the largest organ in the human body. It consists of two primary layers - the epidermis and dermis. The epidermis is the outermost layer of the skin that comes in contact with the surroundings. It is the barrier that protects us from various stressors present in our surrounding such as pathogens, UV rays, and chemicals. Hence, this layer is also termed body armor [1]–[3].

Skin cancer has been observed to be the most commonly observed malignancy found in humans and is 19th most frequently observed cancer around the globe [4], [5]. In 2018, over a million cases of skin cancer were reported with Australia sharing the highest number of incidences followed by New Zealand [5]. The most common type of skin cancer is basal cell carcinoma, squamous cell carcinoma, and cutaneous malignant melanoma (or simply melanoma). Squamous cell carcinoma and basal cell carcinoma are collectively referred to as nonmelanocytic skin cancer (NMSC) [4].

A. Basal Cell Carcinoma

Basal cell carcinoma is the most frequent type of skin cancer observed among humans constituting over 80% of cases of nonmelanocytic skin cancer incidences [6], [7]. However, exact instances are hard to pinpoint as nonmelanocytic skin cancer incidences are excluded from cancer registries. Albeit basal cell carcinoma has been noted to have low mortality rate and rarely metastasizes, it makes the patients vulnerable to other malignancies posing a huge burden for the healthcare system.

Ultraviolet exposure is the most common cause of basal cell carcinoma [8]. Factors such as timing, amount, and pattern of UV radiation exposure play an important role. It has also been observed that the risk of developing basal cell carcinoma is amplified by frolic exposure to the sun during one's developmental years [8].

Basal cell carcinoma develops in the body parts that are most exposed to the sun, majorly head and neck, followed by trunk, arms, and legs [9]. Nodular basal cell carcinoma is the classical form of basal cell carcinoma which appears as an opalescent blister. The capillaries present in the skin also dilate hence giving their purplish cluster look. Surface basal cell carcinoma mostly shows itself as a scaly red patch on the skin surface. The presence of melanin might be the reason for the brown, blue, or black appearance of the lesions in the case of superficial and nodular basal-cell carcinoma.

B. Cutaneous Squamous Cell Carcinoma

Squamous cell carcinoma, one of the most common cancers found in humans, accounts for 20 to 50% of total skin cancers. Squamous cell carcinoma of the skin is also termed as cutaneous squamous cell carcinoma (cSCC) as squamous cell carcinoma might also arise inside the body such as mouth, throat, or lungs [10]. cSCC originates epidermal keratinocyte malignant proliferation. There exist also constitutional and environmental factors affecting its development. Known important factors include chronic sun exposure, immunosuppression, fair skin, old age, male sex and past history of Actinic Keratosis (AK). Actinic keratosis is a skin condition wherein the skin develops rough, scaly patches. Sun exposure is one of the major reasons for the causation of actinic keratosis and without treatment, it can turn into cancer. AK is scrutinized as a premalignant lesion that may develop into an invasive CSCC and also is the most crucial predictive factor for cSCC.

cSCCs are generally completely eradicated via surgery, but even so, there exists a subset of cSCCs that maintain some features that lead to an increased likelihood of recurrence, metastasis, and even death. After surgical excision, the ten-year survival crosses 90% but also drops significantly when metastasis is observed. Taking into account the higher frequency of occurrence of cSCC, it has a considerable effect on overall death caused by skin cancer

Prompt identification of these can aid further workup and management.

C. Melanoma

It has been globally observed that among the cases of primary malignant cancer, newly diagnosed, 1.7% is of cutaneous melanoma.

Converting of melanocytes to malignant melanoma is governed by a complex process that involves the interaction of endogenous and exogenous triggers along with immunogenic factors and tumor intrinsic factors. Even though melanocytes divide less than twice a year, the division rate increases as melanocytes evolve, alongside multiple mutations.

Known risk factors include chronic sun exposure with subsequent tanning, sunburns, fair skin color, and tendency to freckle; also personal history or presence of dysplastic or melanocytic naevi.

Thus, if abnormal skin proliferation is detected at an earlier stage, the survival rate can be up to 96%. However, if detected at a later stage, the rate of survival decreases to 5% [11]. Thus, the early disease detection for skin cancer could reduce the damage caused by the disease. With recent advances in the field of machine learning, medical image processing has been the subject of study for quite some time now with many experts engaged in the study of detection of skin cancer.

Object detection is the ability of a computer to identify and locate one or more effective objects from an image or a video. Skin cancer exhibits telling visual symptoms. Therefore, object detection could be applied to detect potential lesions. YOLO (You Only Look Once) is a real-time object detection algorithm. It combines the multi-step process of classifying and predicting the detected object into a single step. It runs much faster than two distinct neural networks used to detect and classify targets separately.

This manuscript outlines the proposed methodology and obtained results for detection and classification of a given lesion into basal cell carcinoma, squamous cell carcinoma, or melanoma in real-time using YOLOv4 algorithm. Dermoscopic images (images obtained from dermatoscope) as input and gives the predicted area of lesion along with lesion type as its output. Moreover, YOLOv4 object detection algorithm is used as it processes frames 12% faster in real-time than the previous iteration of YOLO model, i.e., YOLOv3 [12].

II. Literature Review

This section enlists the various works done by researchers in this field:

1. Uzma Bano Ansari proposed a method for classification of a given image into cancerous or non-cancerous using Support Vector Machines [13]. In this method, the support vector classifier is fed an image that is obtained from gray level co-occurrence matrix.
2. J Abdul Jaleel and team proposed a computer-based skin cancer detection method wherein dermoscopic images were filtered, segmented using maximum entropy threshold, and were indexed using Artificial Neural Network (ANN) for classifying whether the lesion is cancerous or non-cancerous [14].
3. Megha Biswas and Manjunath Hlremath in their work "Computer-Aided Detection and Recognition of Malignant Melanoma in Dermoscopic Images" proposed a method of hybrid segmentation combining watershed and active contour methods for image segmentation and use of Support Vector Machines to classify lesions as malignant melanoma or otherwise [15].
4. Isha Patel defined a method in her paper "Dermoscopic Image Classification Using Image Processing Technique For Melanoma Detection" to classify a lesion as no cancer, benign melanoma, or highly melanoma [16].
5. Mariam A.Sheha, Mai S.Mabrouk, Amr Sharawy presented a method for diagnosis of melanoma using dermoscopic images using a multilayer perceptron classifier [17].
6. Mahamudul Hasan et al. presented a method for the classification of lesions as benign or malignant using a convolutional neural network [18].

As can be seen, there is research present to classify a given lesion as benign or malignant, no work has been done to further classify the lesion into cancer types. This study is the first of its kind to classify a lesion into the three most common skin cancer types namely basal-cell carcinoma, squamous-cell carcinoma, and melanoma.

This study employs the use of the YOLOv4 object detection model as YOLO can perform classification in real-time and can predict bounding box and class probability using a single neural network which makes it faster as compared to other object detection algorithms. Moreover, during dermoscopy, YOLO can be used for the classification of a suspicious lesion. The pace of detecting a suspicious lesion and accurate categorizing the said lesion are both equally crucial factors in early cancer detection.

III. Proposed Methodology

A. Data Source and Features

ISIC Images archive is used to gather images for Basal cell carcinoma and Melanoma. Since the mAP value for squamous cell carcinoma was not satisfactory, a hybrid dataset for it is created. It has images from ISIC images archives and DermNet NZ. A total of 250 images per class from both repositories are downloaded in .jpeg format and annotated manually by using LabelImg software. Both downloading and annotation comprised the pretraining phase of our model. The entire dataset is then bifurcated into the 9:1 ratio of the training set and validation set for each disease. This resulted in 225 training images and 25 validation images per class. While forming the dataset special attention was given to collecting images with distinct features for every class to make feature extraction more robust which will enable the model to detect outliers with much confidence and accuracy. The prime purpose is to classify the given dermoscopic image into its specific cancer type based on morphology.

B. Image Data and Morphological Differences

ISIC or the International Skin Imaging Collaboration maintain a large repository of skin lesion images curated for developing solutions to reduce the melanoma mortality rate [19]. ISIC aims to create repositories for dermatology and computer science community to help in development of intelligent diagnostic algorithms. Concurrent efforts in dermatological imaging are essential to augment modern-day oncological practices. On similar lines, the DermNet NZ image dataset is also created. Dermoscopic images in this dataset are classified into more classes but are less in number for individuals thus using only it as a prime source could have not served the purpose of training with a high-volume dataset. In this project , the approach is to achieve higher scale image prediction for given lesions with its accurate class. Since general medicinal practices revolve around morphological examination, dermatologists look for some signs associated with it. The following Table 1 deals with it.

TABLE 1. DISTINCT MORPHOLOGICAL FEATURES IN CANCER

Class/ Type	Distinct morphological features
Basal Cell Carcinoma	Arborized, comma-shaped and scattered vasculature patterns, aberrantly red vessels with structureless white red areas, telangiectasias [20].
Squamous Cell Carcinoma	Ulceration, pink keratinized lesions, white perifollicular circles, coiled, looped, serpentine, branched or polymorphic blood vessels, and blood spots. [21]
Melanoma	Blue-white veil, regression, multiple brown spots, multiple colors, broadened network, atypical vasculature, radial streaming, peripheral black dots, and globules [22].

C. Image Annotation and LabelImg

LabeImg is a graphical image annotation tool. For annotation, class is first given to LabelImg, then in each individual image, the target area is enclosed in a selection box, whose coordinates are calculated and the target class is mentioned manually.

This study employs the International Skin Imaging Collaboration's (ISIC) skin lesions repository. However, the repository maintained by ISIC stores the images of skin lesions in an individual folder instead of annotating each of them. Therefore, the manual annotation for each image had to be done. Thus, LabelImg was employed.

D. Model Pipeline and Configuration Files

The network pipeline is explained below:

- We begin by cloning the Darknet repository and adjusting the Makefile therein to enable the functioning of OpenCV and to enable GPU acceleration.
- The training and validation sets are copied into a virtual environment and attached to the Darknet system
- With the training environment set up, the configuration settings are adjusted for a triple class classification problem.
- The model is trained for 6000 epochs, with a weights file being saved after every 1000 epochs for later comparison in results.
- The six weight files are then compared, the comparison metric of choice is the mean average precision (mAP).
- The set of weights with the best mAP at (IoU threshold 0.5) are tested on a test set containing 25 images of each class.

The configuration settings for the YOLOv4 model were modified to suit the three-class classification problem at hand.

- The images were resized to both height and width set to 416, the batch size set to 64, and sub-divisions set to 16.
- The max batches were set to 6000, with steps occurring at 4800 and 5400.
- The filters were set to 24.

E. Mean Average Precision (mAP)

Mean Average Precision (mAP) is an evaluation metric used in object detection. Object detection algorithms make predictions based on bounding box and class labels. The mAP metric compares the coordinates of the ground-truth bounding box to the 2D-coordinates of the detected bounding box and returns a score. Fig 1. Higher the score, higher is the accuracy of the model.

For the calculation of mAP, the overlap between predicted and actual bounding boxes is calculated using intersection over union (IOU).

$$Intersection\ over\ Union\ (IOU) = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

IOU is used to ascertain if the predicted bounding box is a true positive, false positive, or false negative. This classification is done using a threshold value for IOU. The IOU threshold value for this study was taken as 0.5.

F. Recall

Recall is a very important metric when it comes to decision-making in biomedical analysis. Since it is based on true positives and false negatives it provides a better analytical approach to deduce conclusions than accuracy. Fig 2. It is calculated as shown below:

$$Recall = \frac{TP}{TP + FN}$$

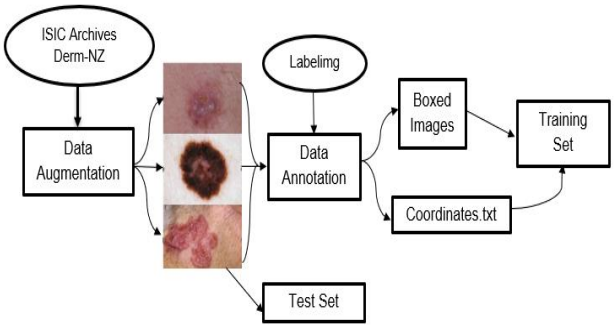

Fig. 1 Data Preprocessing

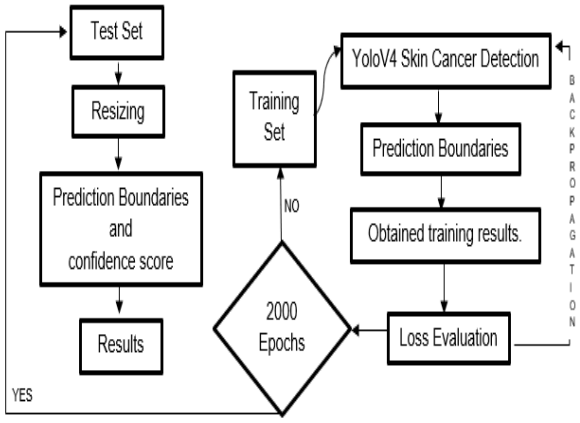

Fig. 2 Model Algorithm [10]

After training melanoma dataset for 1800 epochs 98% mAP was achieved, a similar model was then used for ensemble dataset comprised of different skin cancer images from each class. Fig 3 and 4, It was then trained till 6000 epochs to get the best mAP. Table 2 and 3, The best weights obtained are used on a set of 75 images, 25 from each class as a test set to compute the recall value for metric analysis.

IV. RESULTS

A. Comparative analysis

TABLE 2. PERFORMANCE OF REFERRED APPROACHES

S.No.	Description	Reported mAP	Model mAP	Reference
1.	Detection of Melanoma based on segmentation	97%	98%	[23]
2.	State of the art implementation of YOLO in melanoma detection	83%	98%	[24]

B. Image Classification

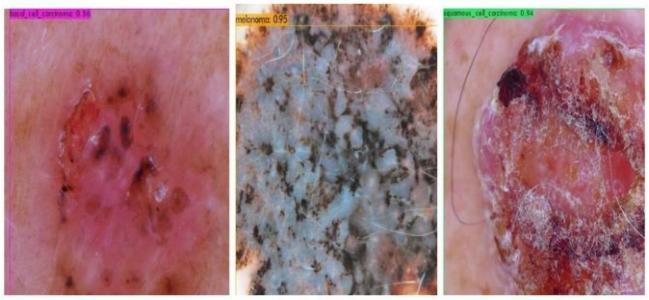

Fig. 3. Left to right: Basal Cell Carcinoma, Melanoma, Squamous Cell Carcinoma

C. Training Loss

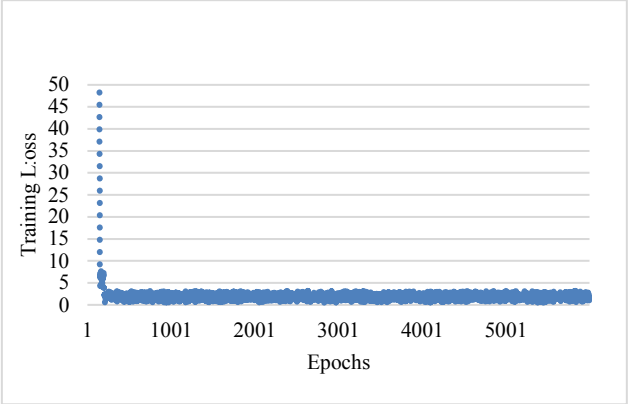

Fig 4. Training loss for YOLOv4 model

D. Recall

TABLE 3. MODEL RECALL

	Basal Cell Carcinoma	Melanoma	Squamous Cell Carcinoma
Recall	0.80	0.72	0.72

E. Mean Average Precision

TABLE 4. mAP FOR MODEL

Epochs	Basal Cell Carcinoma	Melanoma	Squamous Cell Carcinoma	Mean Average Precision
1000	40.3	38.91	9.41	29.54
2000	77.99	88.48	89.79	85.42
3000	58.44	79.56	87.79	75.26
4000	38.36	66.22	51.82	52.13
5000	64.66	77.98	67.41	70.02
6000	61.73	84.33	88	78.02

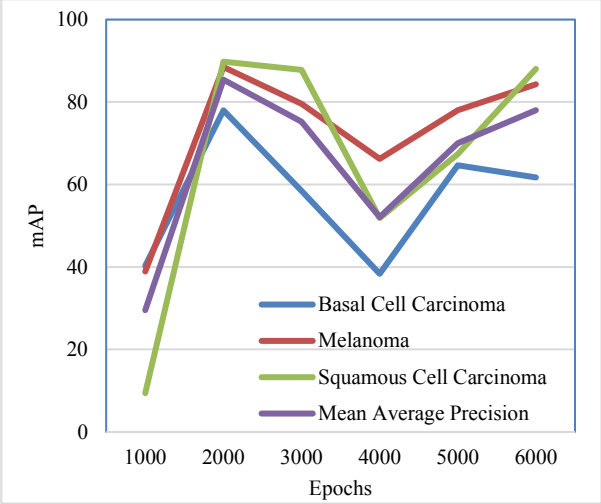

Fig 5. mAP plot for YOLOv4 model

V. CONCLUSION

Immediate diagnosis is the need of the hour to develop a highly resilient and responsive healthcare system. Table 4. This need becomes more profound in the case of cancer as one of the most lethal diseases with socio-economic ramifications. Predominantly computer vision tools developed for diagnostic purposes play a very crucial role in the initial identification of type and class in morphologically distinguishable cancers like skin cancer, shown hereby. The possibility of a biochemical identification method should not be completely ruled out here but with a subsequent rise in population, the burden of disease identification on an already fragile healthcare system is also rising fourfold, especially in developing countries. Fig 5. Thus a combination of deep learning-based throughputs and biochemical analysis should form the base of diagnostics. This paper thus proposes a novel idea with the algorithmic implementation of the YOLOV4 algorithm which is the best version of YOLO developed till now.

This study lays the foundation stone for a multi-class skin cancer classification device. IOT-based sensors can be integrated with the dermatocope equipment which can help dermatologists to detect and classify, tentatively, skin cancer leisons in real-time while performing dermoscopy. Furthermore, this study can be extended to enable the algorithm to detect various other cancer subtypes. This real-time cancer detection could prove to be of incredible assistance as it helps in early detection of skin lesions which further improves the disease prognosis.

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