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Skin Cancer Diagnosis and Detection Using Deep Learning

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Abstract*— If early diagnosis and early detection of skin cancer is achieved, many patients can survive. The traditional method for the public has always suffered from problems such as imprecision and biased results. This study therefore presents a method that can be introduced in a comprehensive workflow to build a healthcare system with artificial intelligence. More exactly an intelligent system that can detect and diagnose skin cancer. While most work that use deep learning techniques focuses either on detection or diagnosis skin cancer, we have use these techniques to develope a model that does both tasks at once. Transfer learning was applied on different models of object detection and diagnosis using a dataset from Kaggle with TensorFlow API. The dataset images are a total set of 3297 dermatoscopic images. To train our model, 2637 images were used. And to test it, 660 images were used. VGG16 was used as an object recognition backbone network (for diagnosis) and Yolo as the object detection framework. The evaluation accuracy of the model was more than 83 %, which is promising.

Keywords*— skin cancer detection, skin cancer diagnosis, deep learning, yolo.

I. INTRODUCTION

Over the past decade, the number of cases of malignant skin cancer has increased significantly, reported by World Health Organization (WHO). It is crucial to detect skin cancer early, this makes it possible to classify symptoms and specialists can decide the best arrangements for the patient [1]. Any time, the process of diagnosing skin cancer has been shown to lead to misdiagnosis due to the doctor's subjective mistakes. Advances in deep learning technology have made it possible to classify and detect skin lesions by adopting deep learning neural network models for object detection [2].

Existing methods such as manual examination according to ABCDE criteria have various limitations due to the different levels of experience of dermatologists and the irregularity of malignant skin lesions, e.g. subjective and inaccurate [1]. So, our work is a contribution to offer a reliable model able for identification and classification skin lesions in real time. When malignant skin lesions is detected earlier, this is associated with improved patient survival. The developed system allows the ordinary user to self-diagnose malignant lesions, in addition to the opinion of the specialist, so that the subjectivity of the conventional diagnostic method ABCDE criteria are met [3]. In order to detect skin lesions, deep neural networks are used to classify and segment it. To achieve this, the deep learning models employed, such as ResNet, are typically complex and difficult to realize, which hinders public access to these processes. Additionally, the ABCDE indications [4]-based skin cancer self-diagnosis method is not practiced strongly by the general public due to its limitations [5].

This study intends to alter the conventional method of treating skin cancer by employing ABCDE indications with object recognition techniques and the deep learning models.

Abnormal growth of skin cells is a sign of skin cancer, it is caused either by high sun exposure or other factors [6]. The main types of skin cancer are divided into two categories, melanoma and non- melanoma. Melanoma skin cancer is considered the most severe of all skin cancers [7].

In some people we can see "moles" called "nevi". They're non-cancerous skin lesions, but they can develop like skin cancer, they manifest under different types[8]. In their work, Lodde et al. [8] has reported that giant moles with an incidence of 2-13% can develop into malignant skin lesions depending on their incidence. Mole appears harmless (benign), but over time it can develop into malignant skin lesions.

When skin cancer is detected early, these helps save lives. Five-year cancer survival has been shown to be strongly associated with cancer diagnosis time period [9]. But also, early detection increase the survival rate of patients [10].

Melanoma grows early horizontally, then vertically over time [11]. Distinguishing melanoma from benign skin lesions at an early stage is a daunting task, even for skin specialists with high experience[12].

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Currently, there is a common method of skin self-examination for detecting skin lesions in first stage, it's the method of the indications "ABCDE", cited at the beginning by [13]. At first, only the «ABCD» tests are considered, the criterion "E" is added for a improved version in [14]. The indications "ABCDE" for the early diagnosis of melanoma are mentioned in Fig. 1. Based on these indications, the more criteria that meet, the higher the probability of skin cancer [5].

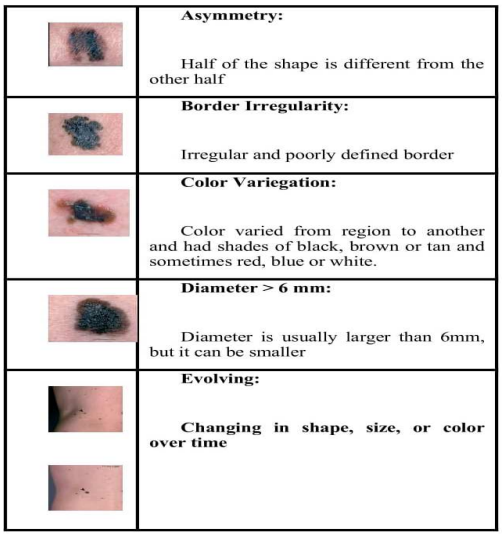

Fig. 1. Skin Cancer Diagnosis by ABCDE Indications.

Along with self-examination by the general public or beginners, some researchers have said that the ABCDE criteria can be used by dermatologists or doctors to obtain detailed information on skin cancer, especially for early stage patients [4], [13], [10], [5]. A proposer of this criteria is Friedman et al. Abbasi et al., who proposed the E criteria, concluded that this method can diagnosis melanoma earlier and can also improve the ability of non-professionals to diagnose the malignancy of lesions. But after examining the criteria, some researchers suggest limitations of this technique and doubt its efficiency [15]. It was revealed that respondents could not distinguish and see the differences between benign skins, such as nevi or moles. A research on the early detection of nodular melanoma Chamberlain et al. [16], has shown that nodular melanoma skin lesions do not sometimes follow the ABCD criteria. A check of the self-diagnosed visual images of a patient's skin concluded that an inexperienced person will have difficulty applying the "ABCDE" indications without the right images[17].

Thus, precise diagnostic tools should be developed to facilitate visual diagnosis and improve early detection results [4].

The computer provides an automated tool that can help lay people diagnose skin lesions, and even assist dermatologists in their intervention [18]. An example of the detailed development of such a tool for the public and dermatologist is given in [19].

II. State of the Art of Deep Learning in Skin Cancer Diagnosis and Detection

Detecting an object get into a classification scheme of an object and the search for its position in a region that surrounds it [20]. Technological advances in various fields such as industry, health and others, have sparked interest in developing object detection methods [21].

Traditionally, the object detection technique is most often performed by manual functions and simple neural network architectures. Deep learning technology is emerging as an important method to overcome the limitations of traditional object detection methods [22]. The deep learning system allows it to learn high-level functions from low-level functions, which can lead to a better classification of objects without manually extracting functions [23]. In deep learning, a known model in image processing is Convolutional Neural Network (CNN) [24].

A CNN contains input data, such as image information, that goes to an orientation to produce other information [25]. Examples of CNN architecture are given in the studies detailed in [26], [27], [28].

Once the layers are created, the entire model must be formed using a labeled dataset to recognize the object [29]. Most often, in all data we find a part of the test data and a part of the training data [30].The two parts complement each other. Learning algorithms was used by CNN to calibrate all parameters (biases and weights). An example of learning algorithm is backpropagation [31]. Overcalibration in training CNNs prevent the model's to well classify invisible data [32]. The problem of over-adjustment was solved by various methods cited in [33], [34], [35]. CNNs are often used to classify an image, such as a popular CNN model known as "VGG16", wich was trained by Pai and Giridharan (2019) for the purpose of classifying seven sorts of skin cancer [36]. CNNs also can be a first network in a networks chain for object detection [21].

Several researchers based their studies on deep learning to diagnose and detect skin cancer [37], [38], [39], [40], [41], [42], [43]. The diagnostic task is usually to diagnose malignant or benign skin cancer. Some researchers use a single CNN for adjust and even for transfer techniques [44], [45], [46]. Nevertheless, other researchers develop their own CNN model [47], [23] or adapt the same CNN model by passing its elements to create another [48], [49].

In this study, we used TensorFlow as a framework. The purpose of this choice is the possibility to distribute calculations to more than one CPU or GPU with a single API [68].

III. Methdology

A. Selection of Object Recognition Backbone Network

Almost all the object recognition backbone networks are related to the classification task [21]. The selection of object recognition backbone networks depends on different criteria [21] such as efficiency and accuracy. A compromise should be made between the two. There are many deeper backbone networks like ResNet [50], ResNeXt [51], and AmoebaNet [52]. The best known are ResNet and VGG [53]. Here, we will use VGG16, because an experience of VGG16 has shown good results [53].

B. Selection of the framework of object detection

CNN is the main skeleton used with a network that allows the detection, and this one serves as a tool to classify and localize the object [21]. Object detectors are divided in two classes, a class of detector two-stage, and a class of detector of one-stage. The difference between them is in the performance and model architecture. The two-stage detector has a more complex architecture, so it is slower, and the other is less efficient [54].

In 2014, Girshick et al. [55] provide a good example of a two-stage detector, it is RCNN that is regions-based. The RCNN is built in three different parts, detailed in [56], [28]. After that, Support Vector Machine (SVM) and also non-maximum suppression (NMS) were used to improve the final detection [57].

In 2015, Girshick suggestted Fast-RCNN [58]. In 2017, Ren et al. [59] developed Faster-RCNN, the best known among two-stage detectors.

In 2016, Redmon et al. [60] developed YOLO (You Only Look Once), the purpose is the detection in real-time. YOLO is faster than RCNN.

One-stage detectors are less accuracy than two-stage detectors but are faster. However, two-stage detectors are more accuracy but more slow [61]. Both detectors were compared by Wu X et al. [54]. Also, Wu X et al. [54] summarized the results by showing that with the same feature extraction backbone, each detector executes in a different way using the same dataset.

Depending on the facts mentioned above and our need to have more detection speed, we are going to use the one-stage detector Yolo as an object detection framework in our project.

Our general methodology is given by the scheme in figure (Fig 2.). Input images contains a folder of benign or malignant images (all lesions), and a folder with images of three lesions, melanoma (MIL), nevi (NV), or basal cell carcinoma (BCC).

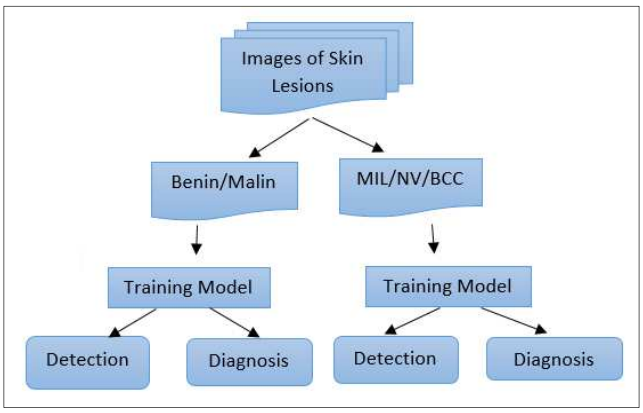

Fig. 2. General Flowchart of our Methodology.

IV. Coefficient of Results Evaluation

Like any researche work, there are problems in detecting objects. Each problem has different evaluation measures [62]. MSCOCO and PASCAL VOC [63] are always used as a reference for object detection [21]. Each of the challenges offer a medium-sized dataset using 20 object detection categories, however the images number in the dataset varies [63]. The first object detection metric is called Jaccard Index or Intersection over Union (IoU) [64]. A high IoU indicates a good similarity between the ground truth box and the predicted box. The IoU formula is:

$$I \circ U = (\text{the ground truh} \cap \text{predicted}) \; / \; (\text{the ground truth predicted}) \quad (1)$$

There are some existing challenges where we can take measurements from challenges such as: PASCAL COV and MSCOCO. These measurements have been used by a lot of research [20], [54], [58], [59], [65], [66], [67].

There is a metric called precision, which is defined as the correct predictions on all predictions and it is used to evaluate the models (tire de state of the art aores [37], [38], [39], [40], [41], [42], [43].

The determination of TP, FP and FN will be used to calculate basic measurements such as "recall" and "accuracy" or "precision", which are very useful in the evaluation of object recognition.

The recall (or sensitivity), and the precision (or specificity), are given by following formulas:

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) = \text{TP}/\text{All ground truth} \quad (2)$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) = \text{TP}/\text{All recognitions} \quad (3)$$

In this study, we have used the recall and the precision to evaluate the diagnosis (object classification).

V. Results and Discussion

The figure below (Fig. 3) shows that among 660 images in the dataset, we got 251 of true negative and 299 of true positive while we got just 49 of false positive and 61 of false negative which means that the results are good depending the high number of true positive and true negative.

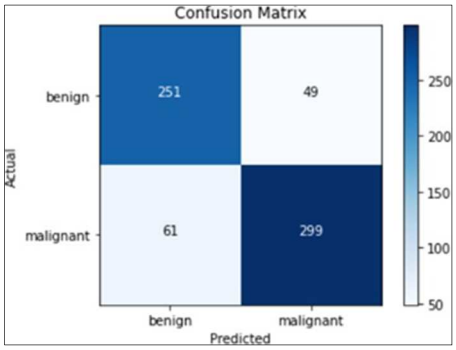

Fig. 3. Confusion Matrix

To confirm that the results are good, we have to calculate the precision and the recall. The figure below (Fig. 4) shows that benign skin cancer diagnosis has a precision of 0.86 (86%) and

a recall of 0.83 (83%) so both precision and recall are high which means that almost all the predicted classes are correct and almost all the objects of the ground truth are recognized. The same for malignant skin cancer diagnosis, the precision is 0.80 (80%) and the recall is 0.84 (84%) which means that the majority of the predicted classes are correct and the majority of the objects of the ground-truth are recognized because of high scores of both precision and recall. We can conclude that the results are good with a high accuracy of 0.833 (83.3%).

The next figure (Fig. 5) is some results of skin cancer diagnosis. The testing model images are selected randomly. The results are good because most of them are classified correctly (the green color) as shown below and as calculated above using confusion matrix, precision and recall.

accuracy
0.8333333333333334
classification_report

	precision	recall	f1-score	support
benign	0.86	0.83	0.84	360
malignant	0.80	0.84	0.82	300
accuracy			0.83	660
macro avg	0.83	0.83	0.83	660
weighted avg	0.83	0.83	0.83	660

Fig. 4. Accuracy and Classification report.

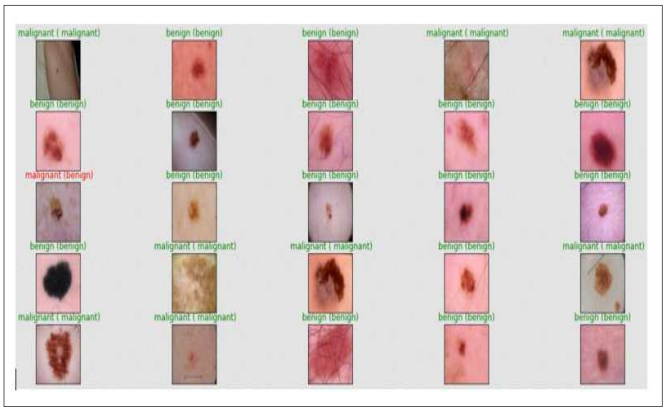

Fig. 5. Testing model by randomly selecting images.

The figure below (Fig. 6) is a malignant and benign skin cancer detection learning curve. The figure shows clearly that the learning curve of all classes learning curve is in the middle between malignant learning curve and benign learning curve which means that the results of skin cancer detection are good.

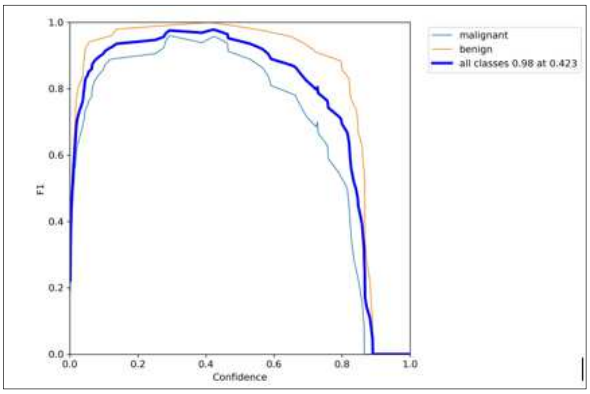

Fig. 6. Malignant and benign skin cancer detection learning curve.

The following figure (Fig. 7) is some results of skin cancer diagnosis and detection. The results of skin cancer detection are good due to the exact detection of the skin lesions as we mentioned above using the skin cancer detection learning curve and as shown below as the skin lesions are localized correctly even the characteristics (shapes and colors) of the skin lesions were very different. The results of skin cancer detection were mixed with the ones of the skin cancer diagnosis to have a complete system of skin cancer diagnosis and detection as shown below in the figure.

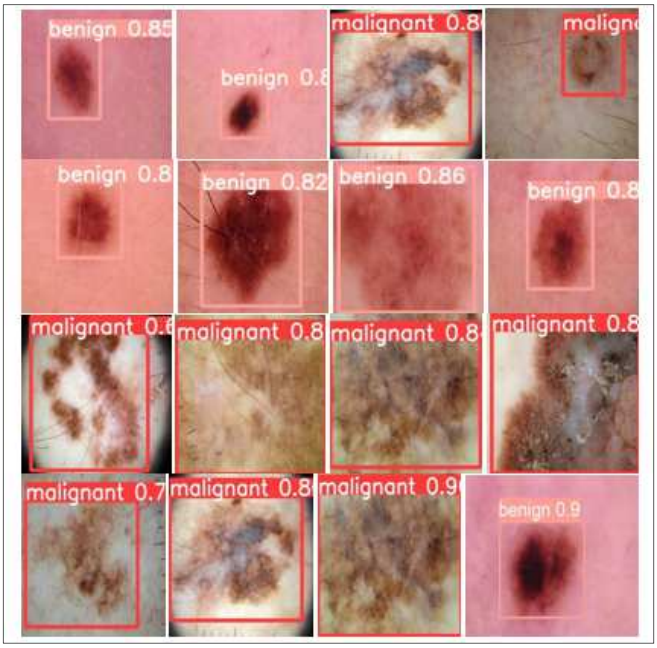

Fig. 7. Malignant and benign skin lesions diagnosis and detection results

VI. Conclusion and Challenges

Throughout this study, it was noted that the majority of existing skin cancer detection or diagnosis studies that used deep learning were conducted separately. In other words, either the model is used to detect skin cancer, using deep learning, or the model is used to diagnose skin cancer using deep learning. Here,

we have unified the two objectives, which were originally distinct, to have a complete system, which detects and diagnoses skin lesions. We tried to use the best available technologies to develop our method, using for example version 5 of yolo, very often cited as perspective in previous studies.

The evaluation coefficient of our results is promising and can be improved. Among the desired improvements, we can either annotate other new data, i.e. use a larger database, or use other data addition techniques. Or, we can use yolo version 7 which can, perhaps, refine our results, because the yolo version is important.

This work remains a contribution to the construction and validation of a comprehensive early detection and diagnosis system. The techniques used in this study can be used to diagnose and detect different types of skin cancer or even other types of cancer such as brain cancer and breast cancer. These techniques can also be improved to be used in other areas such as self-driving systems, face, eye and fingerprint recognition, and defense systems in the military field.

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