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Research Article

A Study of Hybrid Features and YOLO model in COVID'19

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Abstract: Nowadays, Covid '19 disease threatens people's health and life. Accurate detection of Covid'19 is necessary to control its spread. In critical diagnosis, its better to analyze CT imaging than Lab test for fast recovery. Traditional deep learning method has the learning problem which affects the accuracy. In this paper, a new methodology based on YOLOv3 deep learning model proposes to detect Covid'19 in low dose computed tomography lung images. The feature vectors Haar like, HOG, LBP are added to calculate shape and texture of the object. The efficacy of hybrid computational YOLOv3, Haar-like, HOG and LBP features are compared. The sole usage of Haar-like, LBP is less effective, where fast access YOLOv3 features are most promising in multitask schemes. The automatic assessment between the low dose lung CT contents and the clinical semantic terms may help to retrieve reports and medical images from medical database for better diagnostic decision support system. This leads improvement of retrieval accuracy in medical databases.

Keywords: Low dose lung CT Images, Feature Vector, Object Detection, Deep Learning

1. Introduction

The outbreak of Coronovirus Disease 2019 is an unexpected global pandemic with an exponential growth rate and caused large number of deaths declared by world health organization. Coronovirus are mostly spread to animals and mammals and sometimes these infect humans lungs from moderate to serious level. Every day millions of people infected by this virus and spent lot of money, cost and time. Doctors, radiologists and researchers are diagnosing the disease with the help of medical images like X-ray and Computed tomography (CT) images(Shah, F.M., Joy, S.K.S., Ahmed, F. *et al (2021)*). Lung ultrasound imagery is a portable , low cost shown great potential to diagnosing pulmonary conditions (Julia Diaz-Escobar, Nelson E. Ordóñez-Guillén, Salvador Villarreal-Reyes et al (2020)). Hence its clear to develop a novel CAD tool to provide fast screening in places where traditional testing is not effective. Computed tomography (CT)(Murphy, K., van Ginneken, B., Schilham, A. M., De Hoop, B., Gietema, H., and Prokop, M. (2009)) is a test that provides an initial window into pathophysiology that could focus on several stages of disease detection and analysis (Lin Li, Lixin Qin, Zeguo Xu, Youing Yin. et al(2020)).

2.Significance Of The Study

Texture and shape classification techniques are popular to detect specific region of interest objects. HOG and Haar like features are shape feature vector techniques and LBP is texture feature vector method(Dalal, N., Triggs, B (2005)). In recent years, the hybrid features are used to detect object with best accuracy. It can be HOG with LBP or LBP with Haar or Haar and HOG. However the arrival of YOLO family dominates the hybrid feature vector models.

A deep learning model can accurately detect coronavirus 2019 and differentiate it from other lung diseases.Though RT-PCR (Reverse transcription - polymerase chain reaction) introduced by Food and Agriculture Organization can distinctly identify coronavirus disease, it has a high false-negative rate. In Further, many regions of the world RT-PCR's availability is limited. So, medical images such as Computer Tomography (CT) and X-ray images can be the next best alternative to detect this virus as most of the medical or hospital commonly have this device to generate images.

3.Review of Related Studies

CT images (Xu, Danqing, and Yiquan Wu. (2020)) cost more so priority is given to X - ray images. More data can be seen in x ray images and it is economical than CT scan. Even though CT images cost more , it also becomes more convenient to get detailed section of a model. In recent times by studying kaggle RSNA pneumonia data set, COVID'19, X ray data set was considered more. Here hybrid dataset combining COVID'19 dataset and human lung x ray images was trained and examined. Four papers used COVID'19 CT segmentation(Roth, H., R., Lu, L. (2015)) dataset to develop a classification architecture for CT image based works.

YOLO model is introduced in 2015 and later developed into version 2,3, and so on. In this paper object detection is carried using feature vector. Object detection is one of the main part of image processing to detect region of interest. Feature vectors helps to find objects in machine learning techniques. In this object detection technique the considered images is divded into 'n' number of equal dimensional grids in size. Then the detection progress starts from one cell to another from top and continue the detection till it reach the end of the cell. If the object found red window bounding box will be appeared else no bounding box object will be seen. In YOLO the classes can be predicted using the bounding box. In real time videos are inputs and objects can be detected by layers which is faster than other methods.

YOLOv3(Sindhu Ramachandran S., Jose George, Shibon Skaria, Varun V. V.(2018) and Ren, S., He, K., Girshick, R., Sun, J. (2017)) is fast as it predicts objects accurately with highlighted bounding box using mean average precision and intersection over union values which performs by single fully connected layer.

4.Objectives Of The Study

- To detect on COVID' 19 images , whether there is any significance difference between texture feature and shape feature
- To detect COVID' 19 affected area. in CT images, whether there is any significant difference among hybrid feature detection and YOLO detection

5. Materials and Methods

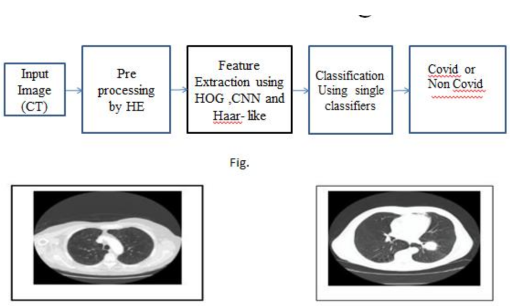

Fig. 2 COVID or NonCOVID detection using Hybrid Feature Vectors

Hybrid Features

In fast object detection(Ren, S., He, K., Girshick, R., Sun, J. (2017)) , researchers are used color , shape , texture as feature extraction in separate(Girshick, R., Donahue, J., Darrell, T., Malik, J. (2014)). The combination of more than single feature extraction terms as hybrid feature extraction.

In this paper, Public dataset of CT COVID and NonCOVID images are used. The below table shows the distribution of images in YOLOv3 method. The feature extraction and object detection is done by YOLOv3 added with densenet or imagenet or selftrans method.

Table 1:Images distribution

Type	NonCOVID-19	COVID-19	Total
train	234	191	425
val	58	60	118
test	105	98	203

Table 2: Patients distribution

Type	NonCOVID-19	COVID-19	Total
train	105	1-130	235
val	24	131-162	56
test	42	163-216	96

* Max CT scans per patient in COVID: 16.0 (patient 2)
* Average CT scans per patient in COVID: 1.6
* Min CT scans per patient in COVID: 1.0

6.Data Analysis and Interpretation

The hybrid feature extraction proved a lot in terms of accuracy performance measures in recent researches in CT images. Hence to find covid 19 detection in CT images , this paper also compared hybrid method in the combination of color + shape, color + texture, shape + texture vice versa.

$$\text{Accuracy} = \frac{TN+TP}{TN+TP+TP+FN}$$

Accuracy represents the number of correctly classified data instances over the total number of data instances.

Deep Learning Model - YOLO in COVID 19

Nowadays all people are struggled with Covid 19, which spoils human life style and economy. In faster world , people definitely need a faster recovery tool. Hence the YOLOv3 (Xu, Danqing, and Yiquan Wu. (2020))architecture helps to detect region of interest from lungs images(Anirudh, R., Thiagarajan, J. J.(2016)). Compare to high dose CT, low dose CT are healthier(Sindhu Ramachandran S., Jose George, Shibon Skaria, Varun V. V.(2018)). Hence the infected person's low dose CT images(van Ginneken, B., Armato III, S. G.(2010)) are the inputs of YOLOv3(Xu, Danqing, and Yiquan Wu. (2020)) architecture and it will split into number of grids. Each grid will seek the pneumonia affected area in lung(Xiaojie Huang, Junjie Shan, Vivek Vaidya (2017)) and it will search through out the CT Scan image. The mean Average Precision or mAP score is calculated by taking the mean AP over all classes and/or overall IoU thresholds, depending on different detection challenges that exist.

The area of overlap is divided by area of union to provide Intersection over union. This ratio definitely gives a good estimate of how close the bounding box is to the original affected COVID area.

Average precision is valued as area under a precision with respect to recall prediction values.When the Limitation of YOLOv3 discussed definitely one thing should mension which is YOLOv3 could not detect small objects like justa pleura in CT images or earliest starting stage of COVID 19. In this study LIDC – IDRI , Luna 16 datasets are taken as datasets.

Functions of YOLO frame work is as below. YOLO splits videos in to frames and takes an input image with 100 x 100. The image frame work divides in to grids say 3 x 3.Then image classification and localization are applied ion each grid . YOLO then predicts the bounding boxes and their corresponding classes for objects found. In phase I , the images is dived into a grid of size 3 x 3 and there are three classes like covid , non covid or pneumonia. The label z will be displayed as below

Table 3 . Classification of objects using classes

Sl.no	p	bx	by	bh	bw	c1	c2	c3
Image 1	0	?	?	?	?	?	?	?
Image 2	1	50	55	100	100	0	1	0
Image 3	1	65	70	100	100	1	0	0
Image 4	1	775	75	100	100	0	0	1

Here, p defines affected area is present or not. bx,by,bh,bw specify the red bounding box of object. c1,c2,c3 are the classes where c1 is covid class, c2 is non-covid class, c3 is pneumonia class. If the no object(Lowe, D. G. (1999)) found the value of p is zero else non zero. In the case of two objects detection in same class then the midpoint is calculated relative to particular grid and the output dimension will have a shape of 3x3x8. So the input image have 100x100x3 dimension. the detected output will be trained as 3x3x8. If more number of objects appearing in the same grid then increase the more number of grids. Intersection Over Union(IOU) dividing intersection area of the two red colour bounding boxes with Region of Interest.

$$\text{IOU} = \frac{area\ of\ overlap}{area\ of\ union}$$

If value of IOU is greater than 0.5 , then the prediction is good. To get better IOU value give more value for threshold. Non max suppression measure took highest probability of detection. For example if the object is having probability value like 0.5,0.4,0,.0.9 . Then 0.9 will be taken as highest probability and 0.5,0.4 are suppressed. Hence IOU and Non max suppression helps to avoid selecting overlapped boxes.

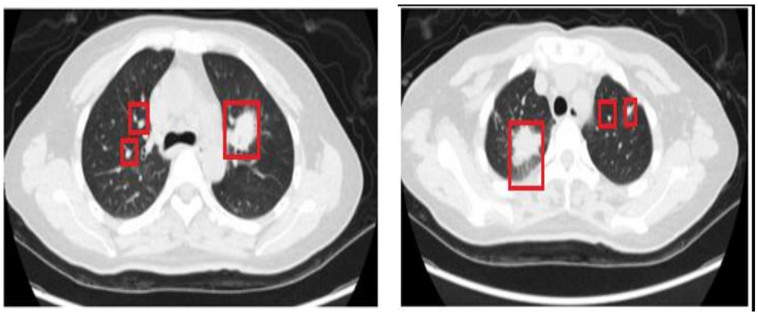

Fig. 3 Sample results of YOLOv3

In the above fig.3, red color bounding box shows the object detected areas. YOLOv3 can identify three objects at a time. If the two bounding boxes within inside then the level set poor, when it merge itself then the level set to good otherwise it termed as bad.

"At 320x320 YOLOv3 runs in 22 ms at 28.2 mAP, as accurate as SSD but three times faster. When we look at the old .5 IOU mAP detection metric YOLOv3 is quite good. It achieves 57.9 mAP@50 in 51 ms on a Titan X, compared to 57.5 mAP@50 in 198 ms by RetinaNet, similar performance but 3.8x faster" by Joseph Redmon and Ali Farhadi.

Ofcourse the statements above said by Redmona and Ali was amazing and worked out very well in this COVID 19 detection study work. When the Limitation of YOLOv3 discussed definitely one thing should mention which is YOLOv3 could not detect small objects like justa pleura in CT images or earliest starting stage of COVID 19. According to performance measure speed YOLOv3 is definitely best compare to hybrid feature vectors.

Table. 4 A comparison between proposed model and state of the art models

Method	**Modality**	**Accuracy %**
Alexnet Loey et al. (2020)	X-ray	66.67
Resnet18 Loey et al. (2020)	X-ray	69.47
ShuffleNet + SVM Sethy and Behera	X-ray	70.66
Googlenet Loey et al. (2020)	X-ray	80.56
CNN Zhao et al. (2020)	CT	84.7
Ying et al.	CT	86
Xu et al.	CT	86.7
Ozturk et al. (multiclass)	X-ray	87.02
Li and Zhu	X-ray	88.9
Hemdan et al.	X-ray	90
Zheng et al.	CT	90.8
Wang et al.	X-ray	92.6

Method	Modality	Accuracy %
UNet + CNN	**CT**	**94.67**
ResNet50Features +SVM	**X-ray**	**94.7**
Fine Tuning of ResNet50	**X-ray**	**92.6**
EndtoEnd Training CNN(Roth, H., R., Lu, L. (2015)**)**	**X-ray**	**91.6**
BSIF + SVM	**X-ray**	**90.5**
DenseNet	**CT**	**84.65**
SelfTrans Model	**CT**	**86.15**
YOLOv3+SelfTrans Model	**CT**	**92.4**
YOLOv3+DenseNet	**CT**	**94.65**

In Densenet Epoch =10.

Average Recall : 86.67%.

Average Precision : 84.26%

Average F1 : 85.45%

Average Accuracy : 84.65%

Average AUC :91.86%

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In Self Trans Model the F1 score as 85%

Accuracy as 86%

AUC as 94%

The framework of YOLOv3 with Densenet outperforms than other methods.

7.Conclusion

In this study object detection by YOLOv3 can be detected as a regression problem and provides the classes with probability. The input images can be given as real time. The prediction can be achieved by single run. The output is an image with bounding or anchor boxes along with identified classes. The state of art method YOLOv3 with Densenet worked well for CT lung images than other competitive methods. The glassy look area is identified as COVID'19 affected area in CT image.

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