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REAL-TIME ABNORMAL EYE BLINKING EYE DETECTION USING Y-UNET

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ABSTRACT

The Yolov5 uses the self-adaptive anchor method instead of the traditional calculation method. Instead of calculating the anchor size based on the dataset label, it can also set the anchor size as a parameter. Unet is popularly used in medical image segmentation. In this article, we will introduce a new approach for the end-to-end extraction of the eyelid. It is a process that involves three steps, namely, de-noising, preliminary extraction, and precise eyelid segmentation. Y-UNet are both useful tools for identifying small targets. In addition, their ability to effectively segment or adhesive eyelid has been optimized. We optimized the overlap between U-Net and YOLOv5 for eye blinking. The objects detected in the yolov5 model that is higher version of Yolo should be masked on the images processed by the U-Net model with color segmentation of each objects. Moreover, in a preprocessing stage we use Kalman filter is very fast and are well suited for real time problems and embedded systems. This filter is a simple algorithm that predicts and separates random signals from noise. It can also detect the presence of noise and prevent it from generating an error. Automatic eye blinking detection is an important component of glaucoma diagnosis. In this research, Human eye blinking ratio calculation mainly used for detection of abnormal eye at early stage using our proposed Y-Unet model.

Keywords: Yolov5, U-Net, kalman filter, sensitive mirror analyzer and retina tracker (SMART) system.

INTRODUCTION

YOLO [1] is a deep convolution neural model that is commonly used for object recognition. It has been developed by the open-source community since 2004.The present implementation uses the YOLOv5s [2], YOLOv5m [3], and YOLOv5l [4] models. Although these are the smallest ones, the larger ones can still provide better performance. There are many types of deep neural networks that are capable of detecting objects. One example is the mask-RCNN. This network is designed to provide a more precise and accurate method for instance segmentation.

Other solutions such as the mask-RCNN [5] could provide better detection performance and better location of the objects. But, the YOLO speed would still allow the task assistant to perform its usual tasks efficiently. To learn how to identify objects, we need to draw a box around each object. This method is used to teach our object detector to predict objects. This paper presents a method to extract and classify eye blinking using the Yolov5 network [6]. We first put the RGB images into the neural network and then output the results. Output the results of the tests with respect to the target face and eye localization for human, eye blinking open close ratio per minute.

The tests were carried out in three different sizes. In addition to eye tracking and face detection, this paper presents an approach to analyze and detect blinking patterns. The method draws on the high temporal detail of event cameras. We use event cameras to detect blinking. By monitoring the distribution of events in the eye regions, we can identify abnormal event spikes. The videos were recorded using an event camera [7]. Each frame was annotated with the face and eyes of the test subject.

The objective of this work is to develop a deep learning model that can be used in augmented reality systems for maintenance. The datasets are create for the training model. The goal is to train the model in different conditions. The YOLOv5s are also test. The Yolov5 uses the self-adaptive anchor method instead of the traditional calculation method. Instead of calculating the anchor size based on the dataset label, it can also set the anchor size as a parameter.

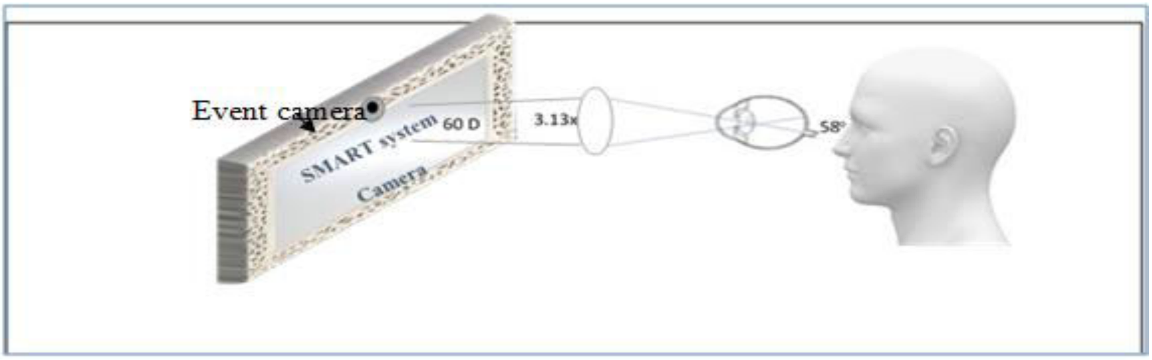

Figure-1. Video processing data collect from SMART system through event camera.

Above the Figure-1, event cameras measure and report when they detect a relative intensity change, which is known as a temporal contrast event. The data collected by these cameras is then encoded in an event format. Instead of using a fixed rate, event cameras sample at a fast pace. They provide an improved quality of just detecting objects. [8] Event data is encoded with the date and time of occurrence of the detected intensity change (DVC). The DVC pixel's sampling rate is proportional to the observed scene dynamics.

2. LITERATURE SURVEY

In a comparison study, the results of which were presented in the following section, revealed that the YOLOv5 network provided better precision and recall than the Mask R-CNN.

Ryan *et al*., [9] identified and track eyes and face for event cameras using fully convolutional gated recurrent Yolo architecture. A lightweight method to detect blinks was also presented. The results of both approaches were tested and verified on test datasets collected manually. At that time, there are no benchmarks datasets that can be compared to compare. However, the results of that paper demonstrated the potential of event cameras for driving dynamics monitoring (DIM).

Liu *et al*., [10] proposed a method for detected the signals of railway lights using Yolov5 neural network. For the study, they built a dataset with train scenes with signal lights, and then train the model with the data. They compared yolov5s algorithm with Vision-based heuristic and CenterNet algorithms. Finally, yolov5s got better results.

Malta *et al*., [11] proposed the model was trained using two different datasets; The YOLOv5s network was able to identify various components of a car engine with high accuracy and recall. It performed well in comparison to the larger model. The outputs were then analyzed, and it was concluded that YOLOv5s can be safely used for detecting objects.

Yang *et al*. [12], the model was developed using YOLOv5 and Tensor- Flow technologies. It can detect if an individual is wearing a facemask. This system collected the video from the camera and identified the objects in it. If the processing speed is considered, the YOLOv5s was a bit better than the YOLOv5x. It also found out who is wearing the mask. This system is mainly used for identifying faces of people who are not direct facing the camera. Amran *et al*, [13] described the use of YOLOv5 deep learning model to classify and detect brain tumors. The results of the investigation revealed that the YOLOv5l model performed better than the YOLOv5m and the YOLOv5s models in terms of tumor classification and detection.

Zhu *et al*, [14] improved object detection method for detecting boulders in planetary images using YOLOv5. The shallow features have also been added to reduce the loss of feature information for small boulders. The attention modules were also used to highlight the important details that contribute to the detection of boulders. The efficient channel attention network (ECA-Net) and the convolutional block attention module (CBAM) attention modules have been combined to provide a comprehensive view of the boulders detected.

Liu *et al*, [15] tested various object detection algorithms by objecting the current widely held yolov3 and yolov4 with the same PASCAL VOC data. The results of the experiments indicate that the yolov5x model has a better performance in terms of mAP, speed, and overall detection speed. It is also suitable for detecting objects of various sizes.

Luo *et al*, [16] detected the location of the object in the images by looking for the bounding box using yolov5 and used a binary classifier like ResNet50 to get rid of the abnormal images. The method was better than the method only used for detection. This method had the best performance. The two-step method is better than the method only used for detection.

Jia *et al*, [17] improved by adding a target detection layer using The YOLOv5 network. The layer was embedded to improve the model's feature extraction ability. The method developed real-time detection of kiwifruit defects using the YOLOv5-Ours model. The YOLOv5 model has been improved to provide faster and more accurate results. The mAP is a measure of the model's quality. The mAP of the YOLOv5 model has reached a maximum of 98%.

Bai *et al,* [18] proposed method involved the use of U-Net and YOLOv3 to automatically extract a chromosome. It achieved this by removing interferences in the micrographs and extracting the entire chromosome.

We know about study of existing research, UNET was used to segment the human eye, and YOLO to detect them. The images were generated through the proposed Yolo and U-net [19] models. They were then processed according to the predefined rules. The images were processed using the U-net and YOLO models. Main limitation of previous research, the image was processed through the Yolo and U-net models individually. The former found the black and white pixel ration in the bounding boxes. The objects detected in the yolov5 model that is higher version of Yolo should be masked on the images processed by the U-Net model with color segmentation of each objects.

3. METHODOLOGY

In this article, we will introduce a new approach for the end-to-end extraction of the eyelid. It is a process that involves three steps, namely, de-noising, preliminary extraction, and precise eyelid segmentation. U-Net and YOLOv5 are both useful tools for identifying small targets. In addition, their ability to effectively segment or adhesive eyelid has been optimized. We optimized the overlap between U-Net and YOLOv5 for eye blinking.

3.1 Preprocessing

In a preprocessing stage, Kalman filter [20] are perfect for systems that are continuously changing. They are very fast and are well suited for real time problems and embedded systems. The filter [21] is a simple algorithm that predicts and separates random signals from noise. It can also detect the presence of noise and prevent it from generating an error. Automatic eye blinking detection is an important component of glaucoma diagnosis.

Video streaming is becoming more prevalent as it allows users to improve the quality of their images. However, it comes with some problems that can affect the operation of video streams. One of these is image degradation due to the presence of noise [22]. The Kalman filter is a function that uses a series of random signals to minimize the estimated error. It does so by detecting the presence of noise or the random signals. The process model is a type of algorithm that shows the behavior of pixel images in video signals.

$$S_{k+1} = as_k + n_k \tag{1}$$

where the noise-free pixel value is given byS_k. It assumes that the signal statistics are constant 'as_k'and the process noise'n_k' is Gaussian. It is desirable to avoid assuming that the noise is distributed and to make the assumption that it is Gaussian. This will make the design of filter classes easier. The process model is used to represent the behavior of video pixels. It assumes that the noise is Gaussian and that the statistics are constants. Moreover, the measured signal is given by

x_k,

$$x_k = s_k + v_k \tag{2}$$

where v_k is the independent additive zero mean Gaussian white noise with variance of s2 v noise-free pixel value represent by s_k.

This filter is a type of measurement filter that uses a sequence of measured values over time to produce more accurate variable estimates. The filter output is outputted by yk, which is the estimated signal at time k. The variance of the signal is defined by σ_k^2,

$$\sigma_k^2 = E(y_k - s_k)^2 \tag{3}$$

The pixel value k is output for each iteration. This function is used to filter the image output for display or analysis purposes.

Kalman filters are used to estimate states based on linear dynamical systems in state space format. The process model defines the evolution of the state from time k − 1 to time k as:

$$x^k = Fx^{k-1} + Bu^{k-1} + w^{k-1} \tag{4}$$

where F is the state transition matrix applied to the previous state vector x^{k-1}, B is the control-input matrix applied to the control vector u^{k-1}, and w^{k-1} is the process noise vector that is assumed to be zero-mean Gaussian with the covariance σ_k^2. YOLOv5 is used to detect eyeid in the video capture image after de-noising.

3.2 Y-UNet Architecture

The Y-UNET model can be divided into three parts: Yolov5, boundary regression and UNet. The first part proposes the boundary box regression. The first part of the model is boundary, which takes the YOLO bounding boxes and feature maps as inputs. The second part generates fixed-size feature maps. The third part, UNet, takes the boundary inputs and turns them into semantic masks in Figure-2.

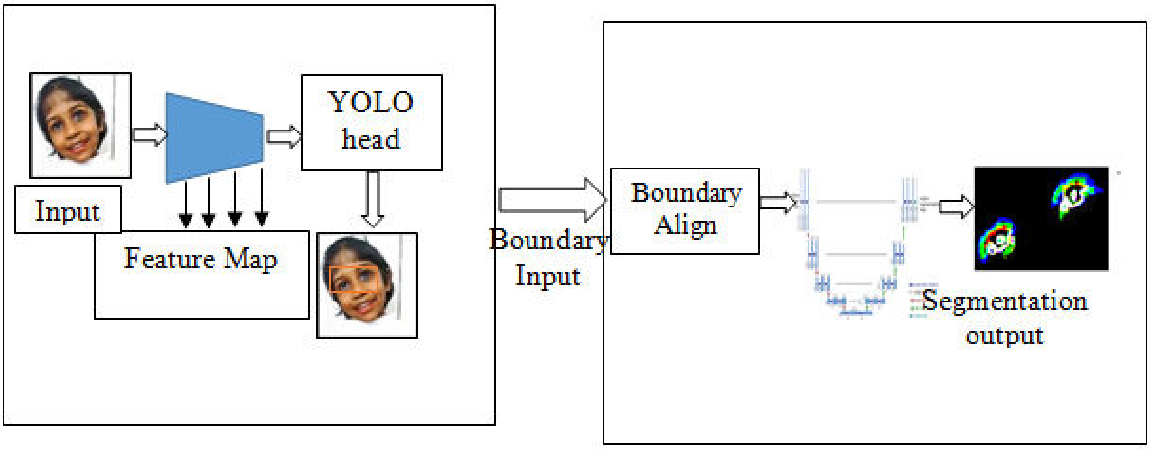

Figure-2. Architecture of Y-UNet model.

Input: Image
Backbones: Bottleneck CSP
Neck: Additional blocks: SPP
Heads: Dense Prediction YOLOv5

The YOLOv5s [18] framework consists of three components, namely, the backbone network, the neck network, and the detect network. The backbone network provides a variety of features and images. The backbone network's focus module is a component that can reduce the calculation of a model's complexity and improve the training speed. The third layer of the network is the Bottleneck module, which is used to extract the deep

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features of an image. It is composed of a Bottleneck layer and a convolutional layer.

3.3 Eyelid Segmentation

3.3.1 Yolov5 workflow

YOLO produces the corners of the rectangle, which are the coordinates of the UNET output boxes. In this paper, we will show how to output the corners of a rectangular image using yolov5v. This method will enable us to crop the image properly. We have to find a threshold first to get the number of pixels that are not zero.

The YOLOv5, YOLOv5n release includes a host of new changes across 465 PRs, with a focus on the new P5 and P6 nano models. The new micro models are very small and can run on both mobile and SMART Mirror. The YOLOv5 micro models are very small and have a slightly improved performance compared to their predecessors. This training is run on a dataset containing over 50 YOLOv5n epochs.

The Backbone uses CSPDarknet [22] to perform feature extraction from images with cross-stage partial networks. Backbone and YOLOv5 Neck rely on CSPDarknet to extract feature data from images. PANet is used to generate feature pyramids networks for aggregation and pass it to Head for prediction. Euclidean distance is more prevalent in larger bounding boxes. Since it affects the size of the boxes, it tends to cause errors. The distance formula is defined as:

$$D(box, centroid) = 1 - IOU(box, centroid) \tag{5}$$

Where D represents distance, box represents the sample, and centroid represents the center of the object, and $IOU(box, centroid)$ represents the intersection of the object's center box and the object box. The final distance can be calculated as,

$$D(box, centroid) = \left[\frac{R_b \cup P_b - R_b \cap P_b}{R_b \cup P_b}\right] \tag{6}$$

where R_b represents the real box, and P_b represents the prediction box.As stated above, YOLOv5-nano algorithm has achieved end-to-end training and high-speed target detection. The Y-Unet network is optimized for multiscale prediction. Its predictions are well-suited for small objects especially medical image. To ensure optimal performance, the network needs to re-cluster based on real application domains.

The good bounding box regressed has three elements: overlapping area, central point distance, and aspect ratio.

$$v = \frac{4}{\pi^2}\left(arctan\frac{w^{gt}}{h^{gt}} - arctan\frac{w}{h}\right)^2 \tag{7}$$

$$\alpha = \frac{v}{(1-IoU)+v} \tag{8}$$

$$L_{CIoU} = 1 - IoU + \frac{\rho^2(b,b^{gt})}{c^2} + \alpha v \tag{9}$$

The formula that is presented in the paper is the same as the formula that was provided in the code. However, the form is different. C CC is the distance between the prediction box (the green c in the picture) and the minimum closure area (the red c in the picture)

$$\alpha v = \frac{v^2}{(1-IoU)+v} \tag{10}$$

$$L_{CIoU} = 1 - CIoU \tag{11}$$

$$CIoU = IoU - \left(\frac{Distancerho^2}{DistanceC^2}\right) - \left(\frac{v^2}{(1-IoU)+v}\right) \tag{12}$$

$$CIoU = IoU - \left(\frac{centerdistancesquared}{convexdiagonalsquared}\right) - \left(\frac{v^2}{(1-IoU)+v}\right) \tag{13}$$

$$L_{YUnet} = 1 - CIoU \tag{14}$$

The Euclidean distance between the rho prediction boxes and the GT box is shown in the figure below.

$$IoU = \frac{A \cap B}{AUB} \tag{15}$$

$$GIoU = IoU - \frac{|C - A \cup B|}{|C|} \tag{16}$$

$$DIoU = IoU - \frac{l_1^2}{l_2^2} \tag{17}$$

$$CIoU = DIoU - \alpha v \tag{18}$$

$$\alpha = \frac{v}{(1-IoU)+v'} \tag{19}$$

$$v = \frac{4}{\pi^2}\left(arctan\frac{w_A}{h_A} - arctan\frac{w_B}{h_B}\right)^2 \tag{20}$$

Correspondence between formula and code Formulas 1, 2, 3 are located in the bbox_iou(box1, box2, x1y1x2y2=True, GIoU=False, DIoU=False, CIoU=False, eps=1e-7).

3.3.2 U-Net workflow

The U-Net network is an adaptation of the Lucene framework. It consists of FC layers that are organized on an auto-encoder scheme. The goal is to get an output that is the same size as the input. The model achieves its goal by sampling a large number of feature channels. The goal is to propagate the multi-scale context information from the images to higher resolution layers. The soft intersection over union (IoU) is used as loss:

$$L_{UNet} = 1 - IoU = 1 - \frac{\sum \boldsymbol{I_t o I_p}}{\sum(\boldsymbol{I_t + I_p}) - \sum(\boldsymbol{I_t o I_p})} \tag{21}$$

where It and Ip are the ground truth mask and the soft prediction mask, respectively, and 'o' is the Hadamard product. This product used in image compression techniques. It works by producing a third dimension for the same square footage.

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3.3.3 The proposed Y-Unet framework

Y-Unet is a framework that provides an object detection and segmentation framework. The framework is mainly used for feature extraction and localization in figure 3.The goal of this design is to provide a multi-scale representation of the abstract representation of U-Net, so that it can be used to segment and detect objects. The following two models yolov5 and UNet are then merged into one single model, Y-Unet. This model can be optimized to minimize the addition of loss functions.

$$YUNet = L_{CIoU} + L_{UNet} \tag{22}$$

3.3.4 Model performance

In this paper, we compare and learn the same model with another example of a Mask R-CNN, which is a type of segmentation algorithm. We compare the speed of our model and the method Mask R-CNN to determine the detection speed of our proposed model. We compare our model and Mask R-CNN against the benchmark dataset and the self-annotated dataset.

When we scale the video frame to a smaller size, the detection speed increases. For real-time 30 FPS detection, we achieved it with a resolution of 320x320.In this study, we try to calculate the mAP for two models. The first one is the object detection IOU>0.5, which is considered as TP.

3.3.5 Blink detection

The proposed face and blinking detection [23-25] video results are included in the supplemental material. The objective of this test was to evaluate the effectiveness of a proposed face and eye detector. The proposed method relies on a small number of datasets and lacks a diverse set of testable targets. Its lack of a standard framework limits the number of tests that can be performed. These algorithms were not designed to perform on complex reconstructions. Instead, they rely on high quality estimates in Table-1.

The video results below are annotated to evaluate the precision of our Retina Blinking Rate algorithm [26]. Face and eye tracking and analysis the test videos were recorded using event camera. The footage was then annotated with the eyes and face labels. Tracking with Kalman filters or other method would improve these results Figure-4.

The Retina Blinking rate has been compiled from various sources. It is an unremarkable condition. In light of the proposed Algorithm, it has been discovered that assuming that the Blinking rate is between 15 and 12 tallies each moment, it is ordinary condition. This examination has arranged 4 batches of tests. The tests are grouped into 4 batches. Test 3 has 20 checks each minute which is unconventional condition.

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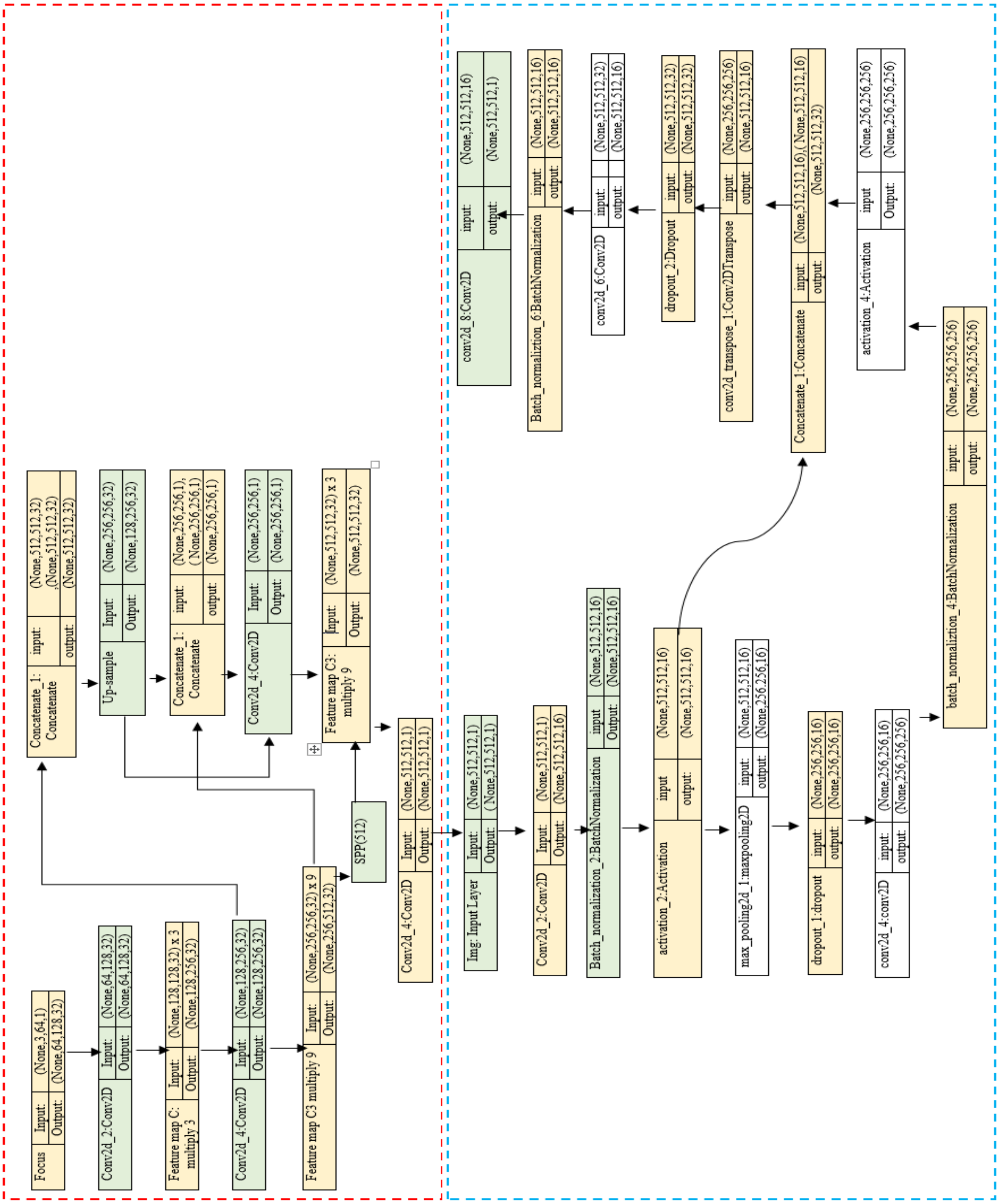

Figure-3. Y-UNet Model.

Table-1. Comparison of mAP and speed for Y-UNet model from existing model.

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Method	RCNN	Faster RCNN	YOLOv3	YOLOv3-tiny	TF-YOLO	Y-UNet
mAP (%)	36.2	67.9	55.9	27.2	31.5	27.3
Run time (sec/img)	0.82	0.26	0.13	0.1	0.09	0.07

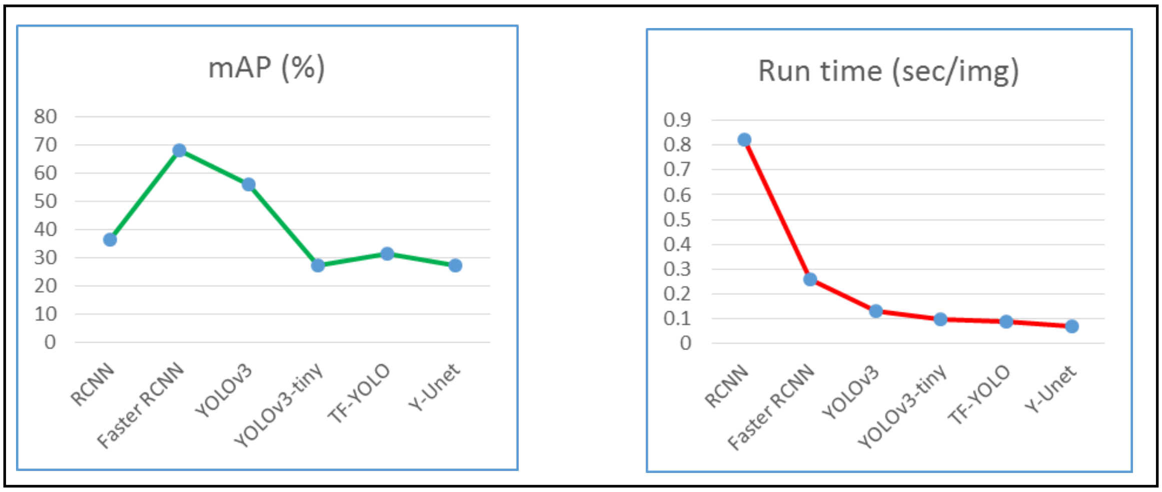

Figure-4. Graphical representation of mAP and speed for Y-UNet model from existing model.

4. RESULT AND IMPLEMENTATION

In this Figure-5, we have isolated asingle blink using a fixed duration window of 5 ms. Using the detected time points from the blink detection methodology, we can model the bimodal distribution and extract eyelid features such as duration, speed, closing time etc. However, the automatic extraction of such features is currently beyond the scope of this paper. Proposed Y-UNet model has been executed using python with jupyter notebook. Correlation of the test pictures are displayed in Figure 5(a), 5(b) and 5(c). furthermore, moreover examined the exhibition on sexual orientation varieties. Finally, this examination have tried to br eak down according to an enlightening viewpoint the information displayed, with the plan to find out certain analogies with the momentum research in the subject of visual perceiver blinking checking rate minutely. The presentation was a lot higher than the staying alive under numerous video characteristics and conditions. The proposed system gave conceivable outcomes FPS is 0.07 sec.

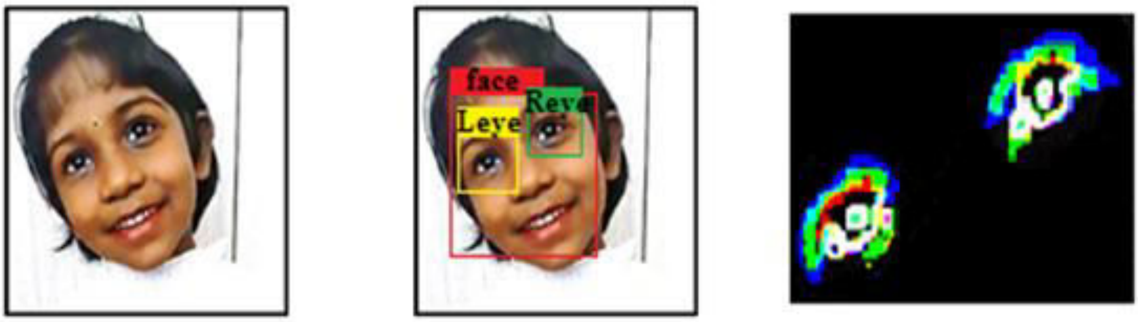

Figure-5(a). Detect and extract face, Left eye and Right eye using our proposed Y-UNet model.

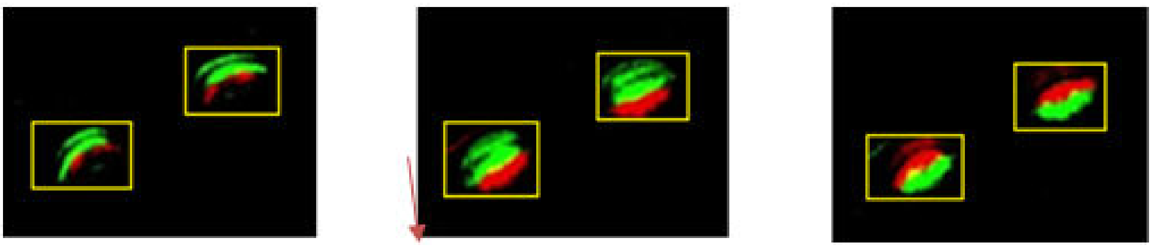

Figure-5(b). Segmenting upper eyelid and lower eyelid when blinking.

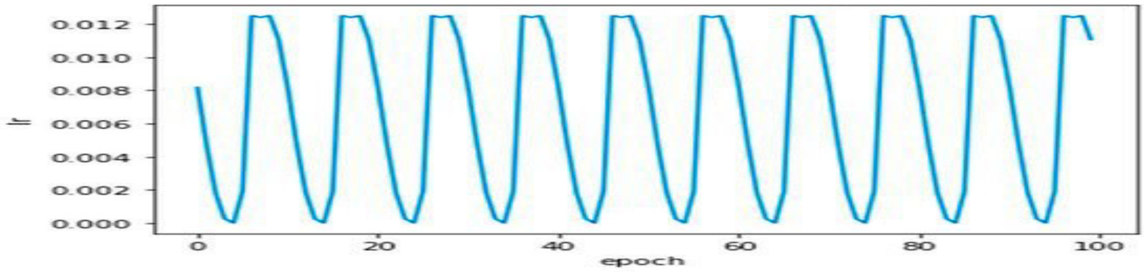

Figure-5(c). Blinking ratio per second.

5. CONCLUSIONS

The Y-UNet network was tested for simultaneous detection and segmentation of objects in an image. It achieved high performance despite having few images with ground-truth. It can perform both detection and segmentation in a single step. These features allow developers to dynamically adapt frame rates to fit various tasks. It also provide a better response to object motion, which can detect blinking signals. Our proposed Ynet model achieves better performance on small target sets with less time consuming due to its use of image features. In this research, Human eye blinking ratio calculation mainly used for detection of abnormal eye at early stage using our proposed Y-Unet model.

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