



Improvement of road safety using YOLO V7 identification.

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Abstract: Road traffic safety is a crucial concern around the world, the probability of accidents and collisions rises as the number of cars on the road grows. Object detection technology has developed as an effective technique for enhancing road traffic safety. This research provides a detailed evaluation of the most current breakthroughs in object recognition systems and their applications in road traffic safety. The paper opens by providing an overview of the issues and risks involved with road traffic, highlighting the importance of enhanced safety measures. It then digs into a full review of object identification strategies, ranging from traditional methods to cutting-edge deep learning models, demonstrating their capacities to identify vehicles, pedestrians, cyclists, and other road items. It investigates how these technologies improve real-time monitoring, collision avoidance, and traffic management. Furthermore, the article looks into object detection for traffic law enforcement and monitoring, emphasizing its significance in improving security and lowering accidents. It outlines prospective future research directions, such as the development of powerful, real-time object detection systems and their application to smart city initiatives.

Keywords: Real-time object detection, road traffic safety, bounding boxes, intersection over Union (IOU), Anchor boxes, non-max Suppression.

I. INTRODUCTION

Every day, millions of lives are at risk on our roads. With the increasing volume of vehicles and pedestrians, ensuring road traffic safety has become a paramount concern. Accidents, congestion, and the loss of valuable time are just a few pressing issues we face. In response to these challenges, this review delves into the exciting realm of utilizing object detection technology to increase road traffic safety. In this inquiry, we will look at how sophisticated object detection systems may change the way we manage and enhance traffic safety. By implementing cutting-edge technology, we can reduce accidents, save lives, and make our roads more efficient. Finding and recognizing items in an image or video is the task of the computer vision technology known as object detection. It goes beyond simple image classification, which categorizes an entire image as a whole, by providing information about the specific objects present and their precise locations within the image. To detect objects with efficiency and speed we are using YOLO i.e. You Only Look Once algorithm. The You Only Look Once algorithm or YOLO for short, represents a ground breaking leap in computer vision and deep learning. Unlike its predecessors, YOLO does not linger over an image, scrutinizing it layer by layer. Instead, it takes a single comprehensive glance and comprehends the entire scene in a fraction of a second. YOLO takes a single glance, instantly comprehending the entire scene in a fraction of a second. This technological innovation has the potential to transform our approach to road safety, providing a proactive and rapid solution to diminish accidents, save lives, and enhance the overall efficiency of our roads. YOLO's swift identification and response to potential hazards make it a promising tool in ensuring the safety of everyone on the roads. With improved accuracy and speed, YOLO v7 enhances traffic management, aids law enforcement, and facilitates the development of advanced driver assistance systems. The importance lies in its ability to reduce accidents, enhance overall road safety, and pave the way for intelligent transportation systems, contributing to safer and more efficient urban mobility. It's really good at quickly and accurately spotting things like cars, people, and obstacles on the road. This helps a lot in managing traffic, making it easier for police to keep things in check, and even assisting smart systems that make driving safer.



II. LITERATURE SURVEY

M. Harshini et al. [1] Using YOLOv7 as the base model, the subsequent technique increases the precision of bounding boxes surrounding objects. Moreover, YOLO employ a grid A bounding box detection technique. An image is used as the input for the Yolov3 algorithm in this method.

D. Balakishnan et. al. In [2] This paper discusses object detection in images, a computer vision problem that involves finding and identifying things inside an image. All objects of interest inside an image are to be recognized and located. In order to develop a reliable and efficient object detection system for use in various real-world applications such as autonomous driving, robotics, and surveillance.

A. P. Jana et. al. In [3] This work focuses on the real-time detection and categorizing of objects from video recordings, which lays a foundation for producing a wide range of analytical aspects, such the total population or the volume of traffic in a given area over time. For each class of objects that it is trained on, the classification algorithm builds a bounding box and produces an annotation that describes that specific type of object.

L. Wang et al. In [4] This work discusses the detection of dangerous objects in an input image. This work proposes a YOLO V7-based algorithm for detecting and counting objects from a single shot. The YOLO V7 detects objects, draws bounding boxes around each object in the image and displays its particular type, counts the bounding boxes drawn around the object, and calculates the number of every individual object.

III. PROPOSED SYSTEM

In the proposed system, YOLO's anchor boxes distinguish objects when numerous centers are present in the same grid cell, ensuring reliable object detection. Accurate detection is enhanced by intersection over union, or IoU, and non-max suppression. IoU compares the real and predicted bounding boxes; a satisfactory prediction is indicated if IoU is greater than a threshold, usually 0.5. To improve object recognition, non-max suppression selects high-probability boxes and suppresses those with high IoU overlap. The bounding boxes of detected items are painted over the image, and gTTS offers vocal feedback for the discovered classes. Additionally, screenshots of frames containing recognized objects are preserved locally for security reasons. YOLO predicts object height, width, center, and class using a single bounding box regression, resulting in efficient and reliable identification. The probability associated with each bounding box indicates the possibility that an object will appear within it.

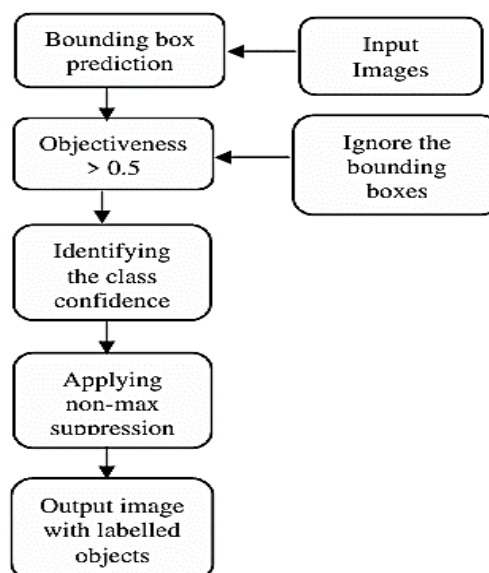


Figure 1..Proposed system



1. Model inputs: a set of images with the dimensions (m, 608, 608, 3).
2. Model outputs: Bounding boxes containing recognized classes, each represented by six variables (p_c, b_x, b_y, b_h, b_w, and c), with c extending to an vector with 80 dimensions.
3. Every picture contains five anchor boxes, resulting in a total prediction of 1805 boxes (19x19x5).
4. Filtering involves eliminating boxes with low scores and selecting the most overlapping box per object.
5. Non-Maximum Suppression (NMS) further refines boxes by calculating IoU, or Intersection Over Union, is the ratio of box intersection to union.
6. As a result, the number of effectively recognized items decreases, increasing overall accuracy.

IV. FLOW DIAGRAM

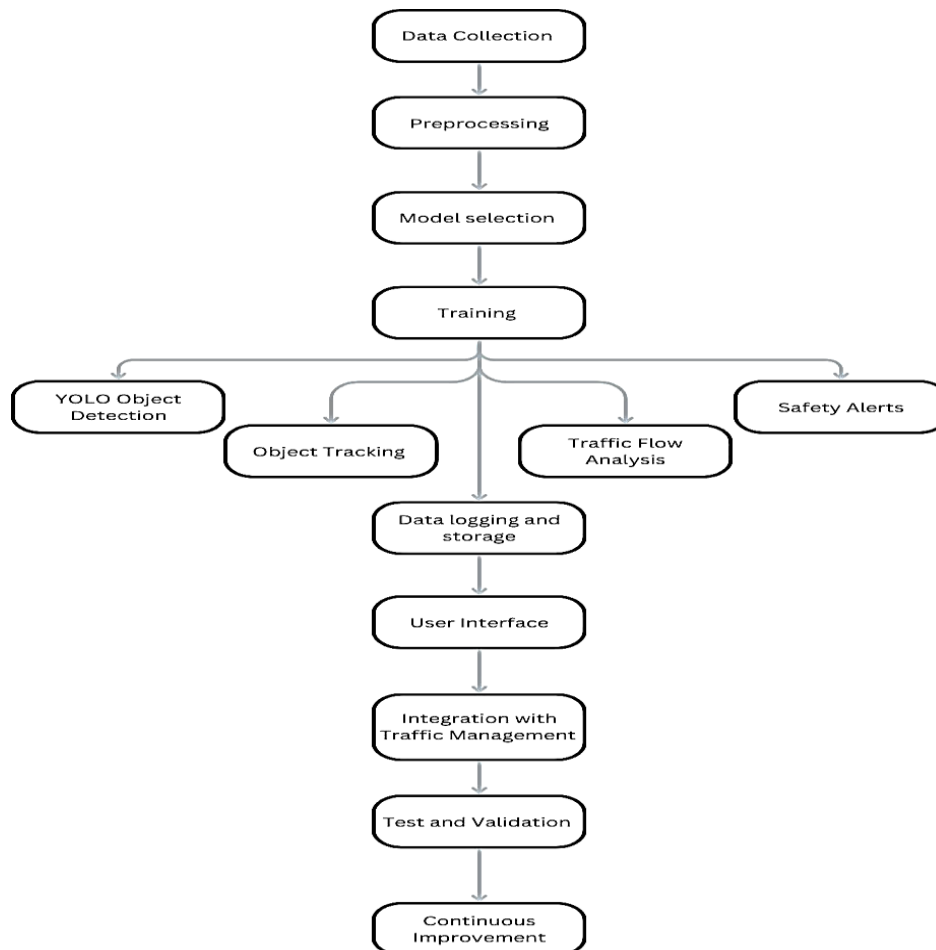


Figure2. Workflow of Object Detection for Road Traffic Safety using YOLO V7

III. PROPOSED METHODOLOGY

The methodology used for research is made up of numerous fundamental components. First, a diverse dataset of road images and videos is collected, including various weather and traffic conditions. After preprocessing the data to ensure consistency, a suitable YOLO model version is selected, taking into account the size and accuracy considerations. The chosen model is then trained on the preprocessed dataset, with a focus on efficient road-specific object detection using transfer learning. The trained model is then applied to each video frame to recognize objects, which are subsequently tracked to monitor movement. The movement and behavior of observed things are examined in order to acquire insight



into traffic flow and safety concerns. This analysis generates real-time safety alerts and a user-friendly interface for system monitoring and control. Finally, the system has been carefully tested across a wide range of real-world scenarios, with continuous enhancement achieved by ongoing monitoring and customization.

Due to its exceptional accuracy and real-time functionality, the YOLO algorithm has gained popularity. One forward propagation cycle through the network is all that is needed for the approach to provide predictions; it just looks at the image once. Following non-max suppression it displays the detected object's name and bounding boxes.

ANCHOR BOXES –Bounding boxes detect just one object in a grid. To identify several objects, we use an Anchor boxes.

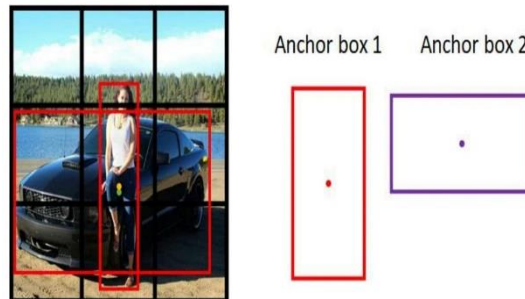


Figure 3. Objects detection using anchor boxes

The picture above depicts the image's anchor box. Notice that both an automobile and a pedestrian are centered in the central cell. Setting the number of anchor boxes to 2 allows each grid cell to detect both pedestrians and vehicles. A pedestrian and an automobile in the same cell will be independently assigned to their own anchor boxes. This is determined by the highest iou value provided by each item and anchor box.

DETERMINING THE PROBABILITY – Next, estimate the elementwise products for each grid, or cell box, in addition their chances that the box has a particular class for each grid. After charting just the boxes with the highest probability supplied by the algorithm, an excessive number of boxes exist., therefore filtering them is critical for accuracy.

INTERSECTION OVER UNION –The intersection over union function is used to test our object detection technique. The iou function computes the area of the intersection of two bounding boxes.

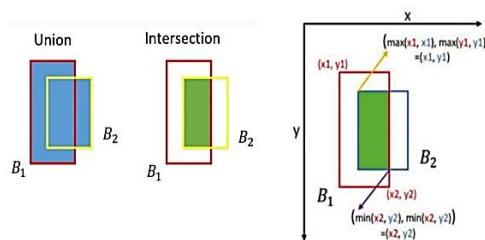


Figure4. Intersection over Union

To do this, we follow two critical steps: Remove any boxes with a low score, which indicate that you are unsure about identifying a certain class. Choose a single box which overlapped numerous other boxes and detects the same thing. Following the filtering based on class score, the left boxes are subjected to the Non Maximum Suppression filter.

NON MAX SUPPRESSION– The stages involved in non-maximum suppression are as follows: • Choose the box with the highest score from the left box selection. • Determine how much it overlaps with every other box, then remove those that have greater overlap than the IoU number. • Go back to step 1 and repeat the process until the box that is now selected has the highest score among all the boxes. This eliminates every box, leaving just the finest box for last.

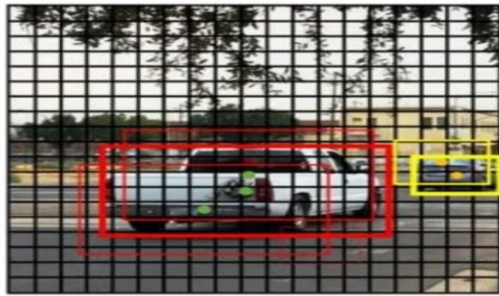


Figure 5. Before Non-Max Supression

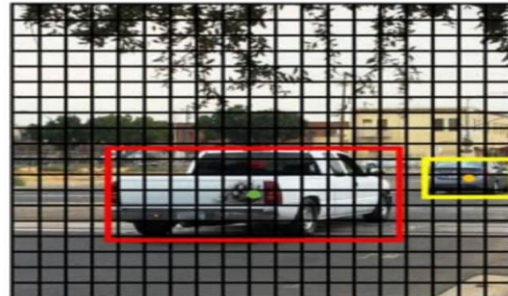


Figure 6. After Non-Max Supression

ELEMENTS OF LABEL Y - In addition to labeling each grid, algorithms for item localization and picture classification are used to each grid. Y is the label's identification. There are eight values in Y. PC - Denotes the presence or absence of an object in the grid. If it's there, pc is equal to 1, else it's 0. The bounding boxes (if any) for the objects are bx, by, bh, and bw. C1, C2, and C3 are the courses. If the object is a car, then c2 would be 1 and c1 and c3 will be 0.

y =	pc
	bx
	by
	bh
	bw
	c1
	c2
	c3

Figure 7. Elements of label Y

GRID WITH NO OBJECT- The first grid in our example picture has no appropriate objects in it. Consequently, it is shown as, The PC value in this grid is zero as there isn't a suitable object.

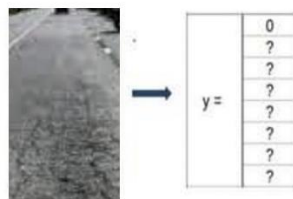


Figure 8. Grid with no object

GRID WITH OBJECT DETECTED - Think of a grid where an object is present.

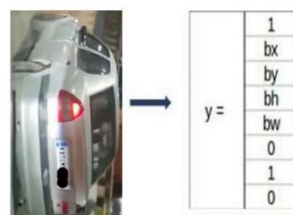


Figure 9. Grid with object detected



The graphic above demonstrates that 1 denotes the existence of an item. The bounding boxes b_x , b_y , b_h , and b_w depict the objects in the sixth grid. The item in the grid is an automobile, the classes are therefore (0,1,0). This produces the matrix $Y=3 \times 3 \times 8$. When an object appears in two or more grids, the object's center point is identified and the grid with that point is selected. To get accurate object detection, we can apply two strategies. First, Non-Max Suppression; second, Intersection over Union. In IoU, it will use the predicted and actual bounding box values. A forecast is deemed accurate if its value of IoU surpasses or is equal to our threshold value of 0.5. Assumptions are all that the threshold value represents.

To improve accuracy or provide a better forecast of the item, we may also use a higher threshold number. The other technique is called non-max suppression; in this strategy, high probability boxes are selected and high IoU boxes are suppressed. Continue selecting boxes until one is chosen; this indicates that box is the item's bounding box.

V. RESULT

Using YOLOv7 for detecting objects, we trained our model on 1,000 different traffic photos, resulting in effective object detection. This improves road traffic safety by correctly detecting cars in real time. Using YOLOv7, we were able to efficiently detect automobiles, as shown in the selected predicted photos below.



Figure 10. Results obtained by YOLO V7 model

VI. CONCLUSION

YOLO V7, a powerful object detection model, can be used in different fields to face real-life challenges. Because of its advantages, the YOLO V7 approach is proposed for object detection in this research. Object detection can be done using any grid. These grid cells predict the observed object border boxes. The system can be further trained to detect various objects and classes in the future, making it applicable to many picture domains. The YOLO V7 model can be adapted for various detection conditions. Our detection system recognizes vehicles, potholes, helmets, and individuals as objects. It may be used for many objects or a single object with a variety of datasets.

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