Enhancing Road Traffic Safety with YOLO V7 Object Detection

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Abstract— Road traffic safety is a crucial concern around the world, as the number of vehicles on the road increases, so does the risk of accidents and collisions. Object detection technology has developed as an effective technique for improving road traffic safety. This study presents a thorough examination of the most recent advances in object identification 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 box, 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 enhance road traffic safety. In this exploration, we will examine the potential of advanced object detection systems in revolutionizing the way we manage and improve traffic safety. By implementing cutting-edge technology, we can reduce accidents, save lives, and make our roads more efficient. Object detection is a computer vision technique that involves identifying and locating objects within an image or a video. 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 (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 REVIEW

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.

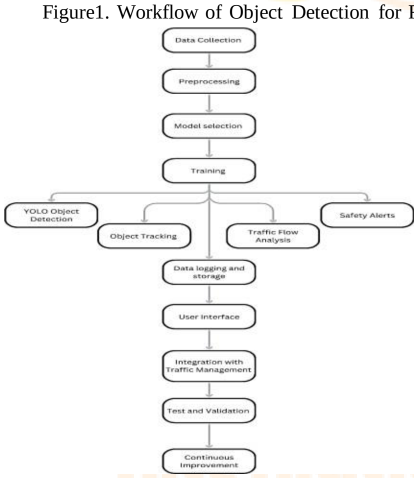
L. Wang et al. In [4] This work discusses the detection of dangerous objects in an input image.This work proposes a YOLO V7-based algorithm for detecting and counting objects from a single shot. The YOLO V7 detects objects, draws bounding boxes around each object in the image and displays its particular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

III. 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.

Figure1. Workflow of Object Detection for Road



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IV.WORKING

The YOLO algorithm is popular due to its excellent accuracy and ability to operate in real-time. The method just looks at the picture once, requiring only one forward propagation run through the network to produce predictions. After 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 Box.

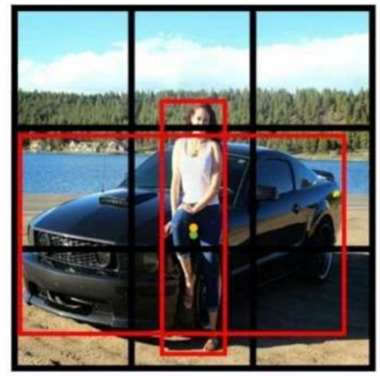

Figure 2. Detection of objects using anchor boxes

The above figure 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 –Now for each grid that is for each box of the cell compute the following elementwise product as well as the probability that the box contains a particular class. After plotting only the boxes that the algorithm had given of higher probability, there are too many boxes and hence filtering these boxes is very important 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.

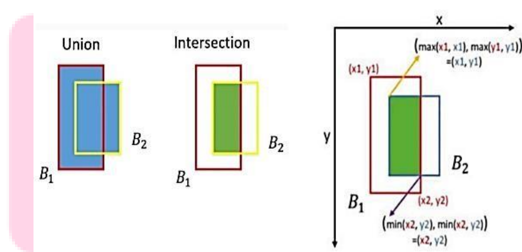

Figure3.Intersection over Union

To do this we carry out two important steps:Get rid of boxes with a low score that is to remove the box which are not very confident about detecting a class.Select only one box that overlaps many other boxes with each other and which detects the same object.After the filtering based on the score of the classes, the second filter which is applied on the left boxes is the Non maximum Suppression (NMS).

- NON MAX SUPRESSION–The steps in non-maximum suppression are: • Out of the left boxes select the box that has a highest score. • Compute its overlap with all other boxes, and discard the boxes that overlap it more than IoU value. • Go back to the step 1 and iterate until there are no more boxes with a less scores than the current selected box..This discards all boxes and only the best box remains in the last.

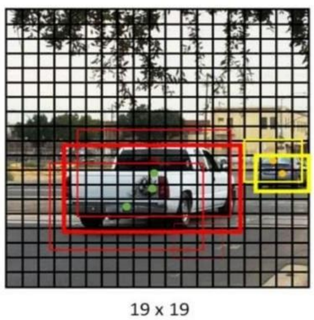

Figure 4. Before Non-Max Supression

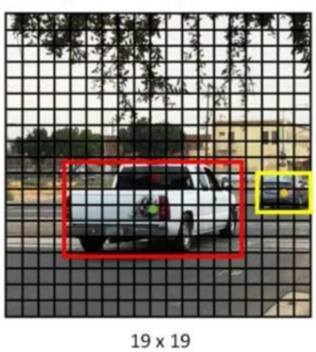

Figure 5. After Non-Max Supression

- ELEMENTS OF LABEL Y -Each grid is labelled along with this each grid undergoes both image classification and objects localization techniques. The label is considered as Y. Y consists of 8 values.
Pc – Represents whether or not an object is present in the grid or not. If present pc=1 else 0.
bx, by, bh, bw – are the bounding boxes of the objects (if present).
c1, c2, c3 – are the classes. If the object is a car then c1 and c3 will be 0 and c2 will be 1.

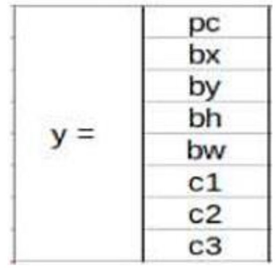

Figure 6. Elements of label Y

- GRID WITH NO OBJECT-In our example image, the first grid contains no proper object.So it is represented as, In this grid, there exists no proper object so the pc value is 0.

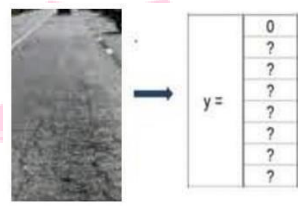

Figure 7. Grid with no object

- GRID WITH OBJECT DETECTED-Consider a grid with the presence of an object.

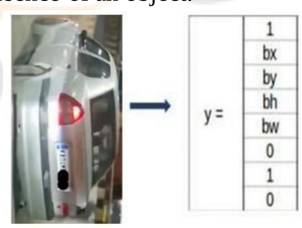

Figure 8. Grid with object detected

The above image shows that, 1 represents the presence of an object. And bx, by, bh & bw are the bounding boxes that represent object in the 6th grid. And the object in that grid is a car so the classes are (0,1,0). The matrix that is formed in this is Y=3x3x8.If two or more grids contain the same object then the center point of the object is found and the grid which has that point is taken. For this, to get the accurate detection of the object we can use to methods. They are Intersection over Union and Non-Max Suppression. In IoU, it will takes the actual and predicted bounding box value.If the value of IoU is more than or equal to our threshold value (0.5) then it's a good prediction.

The threshold value is just an assuming value. We can also take greater threshold value to increase the accuracy or for better prediction of the object.The other method is Non-max suppression, in this, the high probability boxes are taken and the boxes with high IoU are suppressed. Repeat this until a box is selected and consider that as the bounding box for that object.

V.OBJECTIVE

1. Employ YOLO v7 to quickly detect items such as vehicles, pedestrians, and obstacles, allowing for instant response to traffic situations.
2. Identify vehicles, pedestrians, and objects to improve road safety and reduce potential accidents.
3. Create a strong system capable of effectively controlling traffic flow while reducing the likelihood of accidents and ensuring overall safety.
4. Improve the accuracy of YOLO v7 in identifying and categorizing numerous items in complex traffic conditions, resulting in more exact analysis.
5. Use real-time traffic pattern analysis to send out timely alerts and cautions, allowing for more proactive efforts to prevent potential problems.
6. Help to design a comprehensive strategy for minimizing road accidents and improving the safety of all road users.

VI. 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. Intersection over Union (IoU) and Non-Max Suppression improve detection accuracy. IoU compares real and predicted bounding boxes; if IoU exceeds a certain threshold (typically 0.5), it indicates a good prediction. Non-max suppression picks high-probabilityboxes while suppressing ones with high IoU overlap, which improves object detection.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.

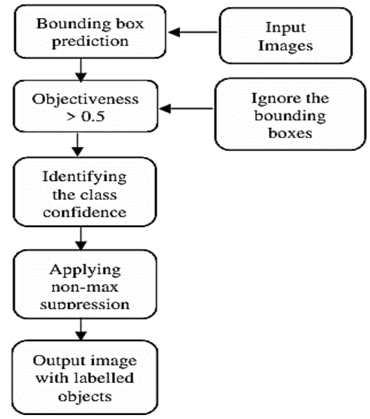

Figure 9..Proposed system

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 80-dimensional vector.
3. Each image 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 Intersection Over Union (IoU), which is the ratio of box intersection to union.
6. As a result, the number of effectively recognized items decreases, increasing overall accuracy.

VII. RESULTS- 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

VIII. 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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