

# Smart City Plan and Execution Using Yolo -AI & ML Trend for Amended Transportation

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**Citation:** Divya B Met al. (2025), Smart City Plan And Execution Using Yolo -AI & ML Trend For Amended Transportation, Journal of Information Systems Engineering and Management, 10(1), xyz,

## ARTICLE INFO

## ABSTRACT

Received: 04 Oct 2024

Revised: 05 Nov 2024

Accepted: 12 Nov 2024

Surveillance is not only in the border security, but it should be local areas that much of awareness should be thought to common man. If we all safe then our nation is also safe, is the slogan of globally developed countries. A smart city is making the country smarter. Tragic deaths are common, and many times the victim passes away but nothing is done about it, resulting in significant losses. AI-based traffic systems are one example of this type of work. Many lives are saved by the real-time medical emergency services that AI and ML family-based traffic monitoring and reporting mechanisms provide to the average person.

**Keywords:** Transportation, Deep Learning, Machine Learning, Traffic Surveillance, Video Analytics, Yolo.

## 1. Introduction

The motive of video surveillance and detecting the pattern of action is became a wide applications in all the fields of life style. Mainly in medicals, crowd analysis and agriculture, why can't we think of use of it in traffic monitoring surveillance and avoid the accident, to save the lives and stable the economic stability of the nation. because millions of money in dollars spent to road construction, either it is of drainage system to highway connection. Traffic maintenance in terms of time, flow, depends on

environment and pattern of the vehicles using the road structure. Heavy vehicle lane is not like our common household circle lanes. Its construction is totally different from ours. More concentration is needed to build it. likewise, roads of north India also same case due to its weather condition detereiot the road very fast and those are not stable for more time .in the machine warning and artificial intelligence era, we have many algorithm s family made many works so easy and faster processing like CNN [1], open cv [4]. Yolo [7]. wisely using these make use in traffic signals in cross junction, to alert urban people to get to know about those, in maintaining residential or industrial, markets places, crowd analysis in airport, office workers or machinery monitoring etc., were not.

## 2. Different ways of detection and identification of accident

Always there is a question, before entering any new topics in the life, like wise. here too, we have to question ourself, why we ned video analytics, hence we lack in dataset to conclude or to get to know about anything, image is better than text data to predict the case, in the same way, videos are better than both of this. To accurately decide what happened, when, the time n season of occurrence and how it happened, totally all w-h question will be

Answered, or at least we can guess the fact. The

Reality will be projected. Surveillance [4] in video analytics best suited presently as:

1. Human beings can't sit for a long time like machine in monitoring the videos like cctv.
2. Laborious work like smart surveillance work can be mad easy.

3. high pedestrian density
4. Tight spacing
5. Unpredictable individual appearances
6. Common partial obstructions
7. Irregular crowd movement patterns
8. Hazardous activities such as crowd panic
9. Detection at both frame and pixel levels.

Likewise, we can use those as big data for future studies, which makes the study of different aspects of detection format, made us to think to make still more advanced one.

CNN [1] is the base for all this studies, where in each video, each pixel of frame from one camera to another varies from many prospect. Because distinguish each picture is tedious job for the different lds, but having same model is used face these challenges made the system to learn double or triple time trained data, hence CNN is widely used in vehicle identification as many times it needs.

Below table shows one of the method of collection of data from MORTH [8], rsa where they collect the coordinate Answer details with spot verification with

**Table .1 rsa data format of patrol system. images captured for further clarification and decision.**

Sl.no	Highway jurisdiction PS name (mys-bng express way)	Jurisdiction (from- to)	Distance
1	Maddur traffic PS	Nidaghatta to Gejjalagere (k.m.f)	15 km
2	Mandya rural PS	Gejjalagere (Saibaba temple) to Ummadahalli gate	10 km
3	Mandya central PS	Ummadahalli gate to Panakanahalli (mg Badavane)	5 km
4	Mandya rural PS	Induvalu to Ragimuddanahalli gate	11 km
Total 41 km of distance			

Singapore's road traffic management system, [7] which combines cutting-edge technology, proactive regulations, and all-inclusive services, is renowned throughout the world for its effectiveness and sustainability. The electronic road pricing (ERP) system, which implements congestion pricing through gantry and satellite technology, is a crucial technique. Erp controls traffic flow during peak hours and promotes the use of public transportation by charging drivers according to their location, time, and road usage. In order to essentially limit the number of cars on the road, the city also implements a vehicle quota system (vqs), which requires potential car owners to bid for a certificate of entitlement(coe).

Smart traffic management technologies like adaptive traffic signal control, which dynamically modifies traffic lights based on current conditions to minimize waiting, are a good complement to these strategies.

At intersections. Using iot sensors and ai-powered surveillance, the traffic management centre (tmc) keeps an eye on the entire road network around-the-clock to ensure prompt reactions to traffic jams or accidents. Reliable substitutes for private vehicles are provided by public transportation, such as a well-functioning mass rapid transit (mrt) system and vast bus networks. Additionally, commuters are empowered to make knowledgeable travel decisions by services

like real-time traffic updates via apps and digital platforms. Together, these strategies and offerings guarantee Singapore's road traffic management is efficient, secure, and long-lasting.

Although text format was used for documentation in the past and is still used today, images and videos are used for greater clarity and precise classification. This includes real-time footage from sensors-equipped highway cameras. To determine the speed, lane detection, number plate recognition, car details detection, and more. A sample of data from state highway patrol and the police department is shown in the table below. Shown in table 1. Data details

3.1 yolo: - uses [6] grid divisions for responsible detecting with calculating confidence and loss function

Yolo v2: - added with k-means and two staged training with fine stage.

Yolov3: -fan used for multi-scale object detection

Yolo v4: - enhanced data set of mosaic, generalized intersection over union(giou), loss function.

Yolo v5: - model size controlling flexibility, and enhancement in data.

Yolo v6: - single object detection and highlighting especially in industrial areas.

Yolo v7: - one fastest with very good accuracy in the result with 155 frames iteration /second

Yolo v8: opencv supported object classification, segmentation, and detection. In a faster rate.in yolov8, as with earlier versions of the yolo architecture, several key formulas and mathematical concepts are applied during the detection process. While the architecture and algorithms used in yolov8 have been optimized for better performance, many of the underlying mathematical principles remain consistent with previous yolo models.

- Here are the key formulas and concepts used in yolov8:

### 2.1. Grid cell and bounding box predictions

• Yolo divides an image into an  $s \times s$  grid. For each grid cell, the model predicts bounding boxes and class probabilities. The number of bounding boxes per cell can vary depending on the model configuration (e.g., 3 bounding boxes). Each bounding box is represented by the following parameters:

- **X, yx, yx, y:** the centre coordinates of the bounding box relative to the grid cell (normalized).
- **W,hw, hw,h:** the width and height of the bounding box, typically predicted relative to the grid cell size (scaled to the image dimensions).
- **C1,c2,...,ckc\_1, c\_2, \dots, c\_k:** class probabilities for each class in the object detection task.
- **Confidence score (ccc):** represents the likelihood that the bounding box contains an object, adjusted by the accuracy of the predicted bounding box. This is calculated as:

$$C = p(\text{object}) \times \text{iou}_{\text{truthpred}} = p(\text{object}) \times \text{iou}^{\text{pred}}_{\text{truth}} = p(\text{object}) \times \text{iou}_{\text{truthpred}}$$

- Where:

- $P(\text{object})$  is the probability that the object is present in the bounding box.
- $\text{iou}_{\text{truthpred}} = \text{iou}^{\text{pred}}_{\text{truth}}$  is the intersection over union (iou) between the predicted bounding box and the ground truth bounding box.

### 2.2. Bounding box prediction formula

• Yolo predicts bounding box coordinates as offsets relative to the grid cell. For each bounding box, the predicted coordinates are:

- **Bx=σ(tx)+cxb\_x = σ(tx) + c\_xb\_x=σ(tx)+cx:** the x-coordinate of the center of the bounding box, where  $t_x$  is the predicted offset,  $\sigma$  is the sigmoid activation function, and  $c_x$  is the grid cell's top-left x-coordinate.

- **By=σ(ty)+cyb\_y = \sigma(t\_y) + c\_yby=σ(ty)+cy**: the y-coordinate of the center of the bounding box.
- **Bw=pwetwb\_w = p\_w e^{t\_w}bw=pwetw**: the width of the bounding box, where pwp\_wpw is the prior width (or anchor box width), and twt\_wtw is the predicted width adjustment.
- **Bh=phethb\_h = p\_h e^{t\_h}bh=pheth**: the height of the bounding box, where php\_hph is the prior height, and tht\_hth is the predicted height adjustment.
- Here,  $\sigma(x)$  is the sigmoid function, which outputs values between 0 and 1:

$$\Sigma(x)=11+e^{-x}\sigma(x)=\frac{1}{1+e^{-x}}\sigma(x)=1+e^{-x}1$$

### 2.3. Iou (intersection over union)

- The intersection over union (iou) is used to evaluate the overlap between two bounding boxes—one predicted and one ground truth. It is calculated as:

$$\text{Iou} = \frac{\text{area of intersection}}{\text{area of union}} = \frac{\text{area of intersection}}{\text{area of union} + \text{area of intersection}}$$

- Where:
- **Area of intersection**: the area where the predicted bounding box overlaps with the ground truth bounding box.
- **Area of union**: the total area covered by both bounding boxes.

### 2.4. Loss function

- The loss function in yolov8 is a weighted combination of multiple terms, which include the following:
- **Coordinate loss**: measures the accuracy of predicted bounding box coordinates (x, y, w, h).
- **Confidence loss**: measures the error in predicting whether an object is present within the bounding box.
- **Class loss**: measures the error in predicting the correct class of the detected object.
- The overall loss function can be written as:

$$\text{Loss} = \lambda_{\text{coord}} \cdot \text{coordinate loss} + \lambda_{\text{obj}} \cdot \text{object loss} + \lambda_{\text{noobj}} \cdot \text{no-object loss} + \lambda_{\text{cls}} \cdot \text{class loss}$$

$$\lambda_{\text{coord}} \cdot \text{coordinate loss} + \lambda_{\text{obj}} \cdot \text{object loss} + \lambda_{\text{noobj}} \cdot \text{no-object loss} + \lambda_{\text{cls}} \cdot \text{class loss}$$

- Here:
- **Coordinate loss**: measures the loss in bounding box location, width, and height, typically using mean squared error (mse).
- **Object loss**: measures the difference in predicted object confidence scores.
- **No-object loss**: applied to grid cells that do not contain any objects.
- **Class loss**: typically computed using binary cross-entropy or categorical cross-entropy loss to compare predicted class probabilities with the true class.

### 2.5. Non-maximum suppression (nms)

- After predictions are made, yolov8 applies **non-maximum suppression** (nms) to eliminate redundant bounding boxes and keep only the best one for each object. Nms involves:
  1. Sorting the predictions by confidence score.
  2. Selecting the prediction with the highest confidence score.

3. Removing all other predictions that overlap with the selected bounding box by more than a certain threshold (usually 0.5).

- The overlap threshold is often defined as the iou threshold:

$\text{iou threshold} = 0.5$

- If the iou between two bounding boxes exceeds this threshold, the lower-confidence prediction is discarded.

### 3. Yolo results

Using bounding boxes and confidence scores, YOLO analyzes every video frame to determine the location and categorization of these objects. Through the identification of damaged vehicles, displaced barriers, or other hazards, this analysis aids in determining the accident's severity. Additionally, it can monitor the motion of objects both prior to and following the collision, offering important insights into the chronology of events. Reconstructing accidents, assigning blame, and improving traffic safety measures all depend on these findings.

Now implementing the process with yolo for sample data of images



**Fig 1. Broken barricade from hit of the heavy vehicle**



**fig 2.a. Car accident side view**



**Fig.2b. Car accident pic from front side view**



Here's how we move forward with accident analysis:

3.1.How to examine the picture:employ object detection software, such as yolov8, to determine:

- The car or cars in question.

The vehicle is damaged. Environmental information, such as adjacent obstacles, objects, or other cars.

3.2.Recommended resources:

- YOLOv8: determine the extent of vehicle damage and identify objects in the picture.
- Python libraries: for visualization, use matplotlib, cv2 (opencv), and ultralytics (for yolo).

3.3.Results:

- Vehicle damage (such as a crumpled front) and environmental impact (such as broken barriers and off-road positioning) would be identified by the analysis. This data may aid in determining the severity.

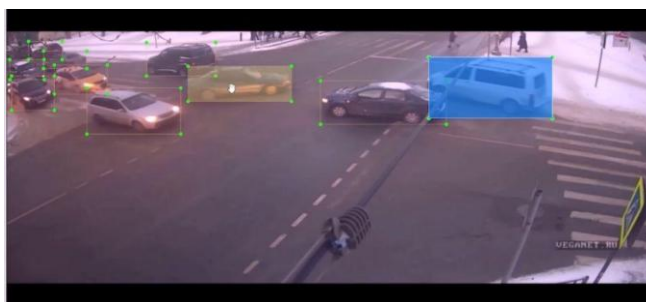
Another examples of task are from live stream of video accident from the highway cc camera footage.



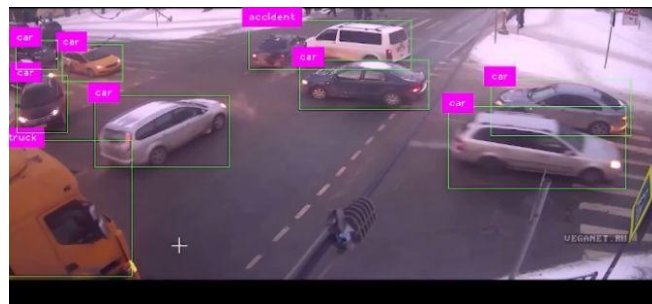
**Fig 3. Mapping the vehicles direction and plotting their direction of movement.**

The car appears to be moving to take a turn, but the front vehicle does not have a view of the opposite vehicle. According to the video, there might be a front side hit. Let's continue processing in Figure 4.4. The likelihood of an accident occurs when a front-end or rear-end vehicle turns on the wrong side..Fig. 5 . Detected the accident from car in the lane vehicle from opposite vehicle wrong turn . From yolo v8 the accident is identified . And marked as blue highlighter , suspect with yellow mask . It was a prediction . But the accuracy is 85%. So, the result is finalised with accident identified and detected.

Each frame of pic is highlighted by class : vehicle, type of vehicle : is also identified .



**Fig.4. Probability of accident**



**Fig 5. Accident detected.**

The performance of crash detection can be impacted by object detection accuracy, particularly in cases of minor auto accidents.

However, detection and conclusion are not enough; we also need to consider more sophisticated ways to implement, such as installing solar maps at night or performing repairs, as busy drivers might not notice the sign boards or someone might strike the board. All users of the road are alerted to the village-to-town crossing. Not all accidents are between cars; they can also involve cars colliding with people or animals, crossing lanes, colliding and flipping over from a flyover to a service road, or involving opposite-lane vehicles, which occurs more frequently than a typical direct collision. T-rate. That needs to be addressed. Thus, in general, yolo v8 and CNN are providing a wonderful service to society.

#### 4. Conclusion

A vision-based detection framework for various types of traffic patterns and accidents was proposed in this paper. Yolo family v8, a deep learning model, is trained to identify objects in traffic environments. As of right now, its threshold value is set at 92% because it completed with 87% accuracy. Further work is decide to carry on alert system and gis help for the layman use , to help their ease of journey,

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