

Accident Prevention System using Deep Learning

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ABSTRACT

Most of the Accidents Occur in these days are during the night time. As per the Reports of the Accident, Most of the Accidents are due to Improper vision of the Drivers during the night time. In order to minimize and prevent the Accidents we came with a Deep Learning Model which Continuously Monitors the Road in the Range of 20 Meters and Specifies if there are people or Animals passing across the Road. The Significance of the project is to help the innocent people who might lost their lives due to the Accident without their intervention.

The Model is also useful for the animals detection . The main purpose of the project is to detect the humans or animals like dog at night and dim light conditions. As the light intensity during night is less, Even our human eye cannot detect a person. The existing system are less effective due to the less accuracy of algorithms such as YoloV2 and YoloV3. The night vision systems indeed work on mainly image processing with assistance of camera and processing units. In this way the problem of detection in case of Night vision is reduced to greater extent. This helps the Driver to reduce the accidents rates in the dim lights.

KEYWORDS: Night Vision, Machine Learning, Coco dataset,YoloV4Algorithm.

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I. INTRODUCTION

Road Accidents is a very serious and high priority public health concern as people die each year as a result of road crashes. Different risk factors such as Speeding, Drunk drive, No safety equipments, Distracted driving, Unsafe Vehicle, Improper vision may cause accidents. With the advancement in the fields of Deep learning we are able to make our device smarter. Traffic surveillance cameras are already installed in almost every part of the city. There are different techniques of classifying the Image such as CNN and K Means .CNN algorithm is majorly used for the Object detection.

In addition to its benefits, CNN also has certain drawbacks, such as the need for a large training data set that adds accuracy, the length of time required for training, the difficulty of encoding images after they have been decoded, and the final image's improper orientation.

So on the subject of all these factors the proposed model is Yolov4, It is abbreviated as You Only Look Once as name suggests it performs the object detection as the Image given into the input. It is one of the fast algorithm, Yolov4 is the improved versions of the Yolov3 , Yolov4It operates on a CSPNet strategy of dividing DenseBlock consisting feature map in two halves and then merging them together via cross-stage hierarchy.

In this study, various machine learning algorithms such as K Means Clustering, Adaboost Algorithm, Convolution Neural Network and YoloV4 are being implemented to identify the Person from dataset which is extracted from kaggle and detect the person or animal based on the video.

The content flow of this research paper goes as follows: Section II is regarding Literature survey, Section III about methodology, Section IV deals with results and Section V ends with the conclusion.

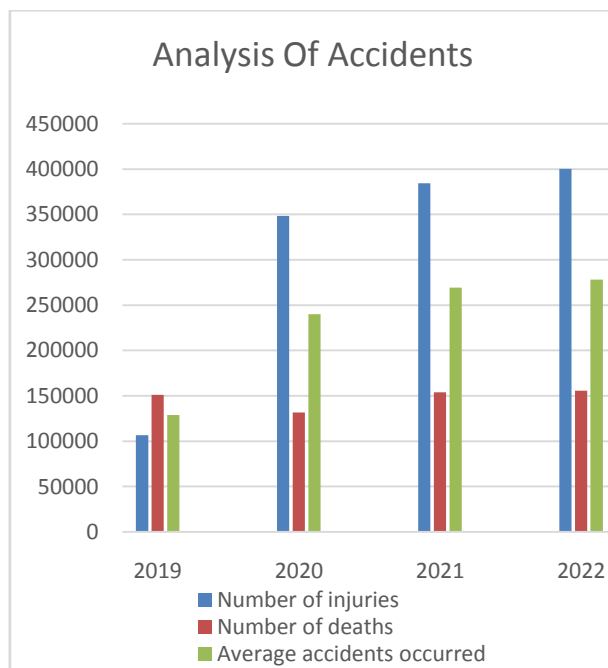


Figure 1. Analysis of Accidents

According to Ministry of Road transport and Highways, It was recorded that the number of injuries caused due to the accidents in the year 2019 on the average was 100000 and In the year 2020 there was rapid increase in the injuries caused it was about 350000. In the year 2021 and 2022 there was slight increase.

The number of deaths recorded were about 150000 in the year 2019 and it was seen that deaths was decreased in 2020 compared to 2019. In the year 2021 and 2022 there were almost same number of deaths caused.

The Average number of accidents occurred was observed that there is rapid increase from 2019 to 2022. Even though the Electric vehicles and Autonomous Vehicles was introduced the accidents occurred were increased.

II. Literature survey

There are several reasons why accidents happen, including drowsy driving, low light levels, and other situations when the vehicle is going too fast for the conditions. Here, our focus is on the low light levels that prevail at night. The traditional method of recognising pedestrians, which has been the subject of numerous studies, involves characterising the pedestrian and their key characteristics before using those characteristics to train classifiers that can tell pedestrians apart from other objects in an image frame.

Dalal and Triggs introduced a landmark algorithm for pedestrian recognition after Traditional approach in 2005. Based on HOG characteristics and an SVM classifier, a detection.

Another method of classifying the individual is by using the Two Stage Detection Framework. R. Girshick's 2014 proposal for RCNN detection starts with using selective search to create a region suggestion box on the image, followed by the use of CNN for feature extraction, training of the SVM classifier, bounding-box regression, and prediction of the outcome.

Other models exist, including Yolov3, Mobilenetssd, and Resnet Models. Resnet was neither accurate nor quick, Yolov3 was accurate but slow, Yolov3 tiny was fast but lacked accuracy, therefore Yolov4 ended up being the best option. Mobilenetssd provided higher speed but lacked precision.

Algorithm	Speed	Accuracy
Resnet	Less	Less
Mobilenetssd	High	Less
Yolov3	Less	High
Yolov3-tiny	High	Less

Yolov4-tiny	High	High
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III. PROPOSED SYSTEM

In Early stages there are various ways of detecting persons or things in a video using popular algorithms such as CNN, RCNN, SVM and HOG (Histogram Oriented Gradient) but in the proposed system we are using the YOLOv4 algorithm which is proposed by Alexey Bochkovskiy in 2020. The advantage through this model is Multiple detection is available and fast detection is also available, backbone basically uses CSPNet structure proposed by Wang. The schematic diagram of applying CSP to ResNet is shown in Figure which adds a path to each cycle block.

The trained model we are utilising in this case is Yolov4-tiny, which is the fourth iteration of the well-known You Only Look Once model that prioritises speed above accuracy. Joseph Redmon created Yolo, one of the top real-time object identification models.

A. Datasets

A dataset is a collection of data that is used to train the model. A dataset acts as an example to teach the machine learning algorithm how to make predictions. The common types of data include:

- Text data
- Image data
- Audio data
- Video data
- Numeric data

The Kaggle dataset of numerous photos of pedestrians or people strolling on the streets and footpaths is the one we utilised in this article.

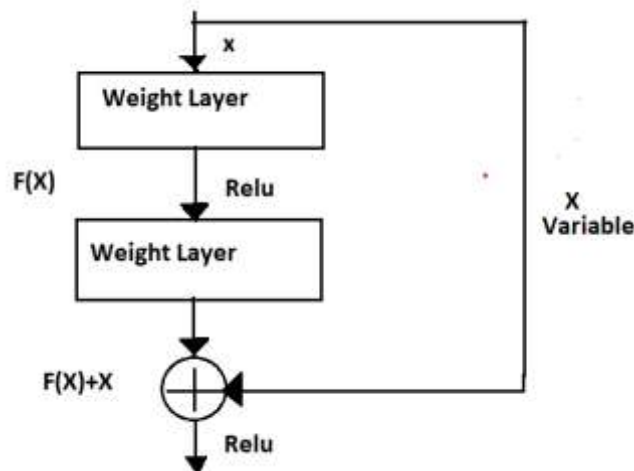
We can obtain a model with high speed and decent accuracy thanks to the extensive dataset.

B. Algorithms

In the Yolov4-tiny is more efficient because in Yolov4 is trained 129 Pre trained Convolutional Layers and in Yolov4-tiny there are only 29 Convolutional layers, It was implemented in Keras framework and converted to TensorFlow* framework. This model was pre-trained on COCO dataset with 80 classes.

1. Resnet:

Shaoqing Ren, Kaiming He, Jian Sun, and Xiangyu Zhang introduced the popular deep learning model known as Resnet in their study. With the advent of these Residual blocks, the issue of training very deep networks has been resolved, and the ResNet model is built up of these blocks.



The first thing we can see in the above diagram is that there is a direct connection that skip one model layers. The core of leftover blocks is a connection known as a "skip connection." This skip connection causes the output to differ. Input 'X' is multiplied by the layer weights in the absence of the skip connection, and then a bias term is added.

2. Mobilenet:

MobileNet is a type of convolutional neural network designed for mobile and embedded vision applications. An object detection model called MobilenetSSD uses an input image to determine an object's bounding box and category. Advantage of Mobilenet is As a lightweight deep neural network, MobileNet has fewer parameters and higher classification accuracy.

MobileNets are small, low-latency, low-power models parameterized to meet the resource constraints of a variety of use cases. They can be built upon for classification, detection, embedding, segmentation.

3. Yolo V3:

YOLOv3 (You Only Look Once, Version 3) is a real - time object detection algorithm that identifies specific objects in videos, live feeds, or images. The YOLO machine learning algorithm uses features learned by a deep convolutional neural network to detect an object.

YOLOv3 has the advantages of detection speed and accuracy and meets the real-time requirements for object detection. YOLOv3's benefits include YOLOv3 is rapid and accurate in terms of mean average precision (mAP) and intersection over union (IOU) values.

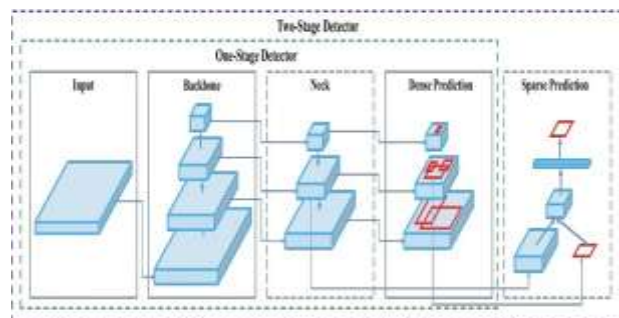
Yolov3's drawbacks include its inability to recognise and separate small things in photos where they appear in clusters because each grid can only detect one object at a time. As a result, YOLO has trouble locating and detecting little items that ordinarily form groups, like a line of ants.

4. Yolo V4:

The Yolov4 algorithm is primarily used for quick object detection in video, picture, and image frame sequences. The fourth model in the You Only Look Once family is called YoloV4.

Models for object detection are retrained to scan a picture for a certain subset of object types. When discovered, these object classes are placed inside the bounding boxes and given a class designation.

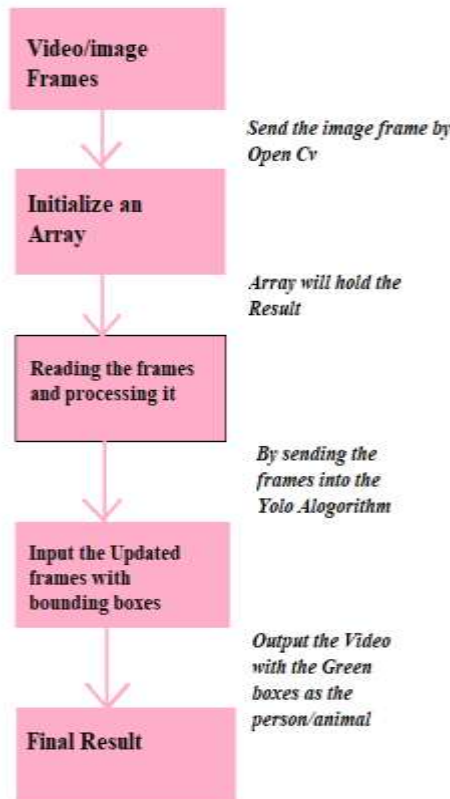
The COCO dataset can be used to train object detection models. The dataset provides bounding box coordinates for 80 different types of objects, which can be used to train models to detect bounding boxes and classify objects in the images.



The main advantage of YOLOv4 is twice as fast as EfficientDet (competitive recognition model) with comparable performance. In addition, AP (Average Precision) and FPS (Frames Per Second) increased by 10% and 12% compared to YOLOv3.

C. Work Flow

Through a flow chart, we can easily navigate through each step of the project's operation, from collecting images from the cameras to initializing an array to store the results to passing frames to the yolo algorithm, updating the frames with bounding box, and finally alerting the driver by beeping an alarm.



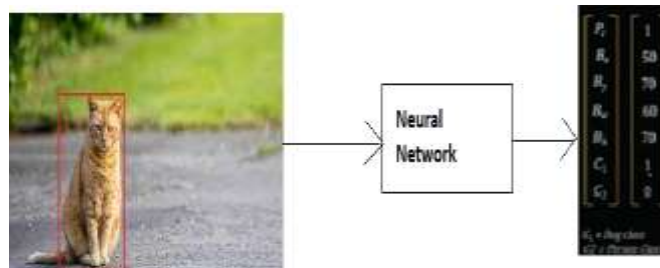
IV. IMPLEMENTATION:

Yolo algorithm which stands out from the other algorithms like RCNN, Faster RCNN because of its high speed, high accuracy and simple architecture.

Before looking at the working model let's understand how object localization actually works.

Using a Neural Network for Object Localization.

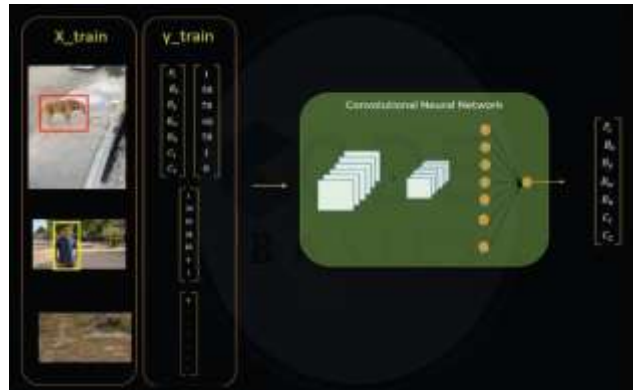
Let's try to understand what the output vector represents:



Here output vector size is 7 with the below indications.

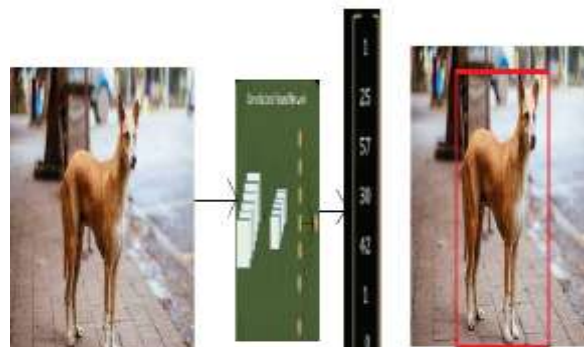
1. P₀ indicates whether any object of interest is there or not in the image.
2. B₀ to B₃ indicates bounding box coordinates.

3. C1 will be 1 if the object detected is a dog otherwise it will be 0.
4. C2 will be 1 if the object detected is a person otherwise it will be 0.
5. So for training, we should give images with bounding boxes as x_{train} and its corresponding output vector as y_{train} for the neural network.



As previously indicated, the neural network will be fed a large number of images together with their ground truth vectors.

The trained neural network will predict the object's class and position when given a new image as seen below.



As $C1$ in the output vector is 1, the object predicted is of class dog and its coordinates are predicted as $[25, 57, 30, 42]$.

But what if the image contains multiple objects. So how do we choose the size of the output vector?

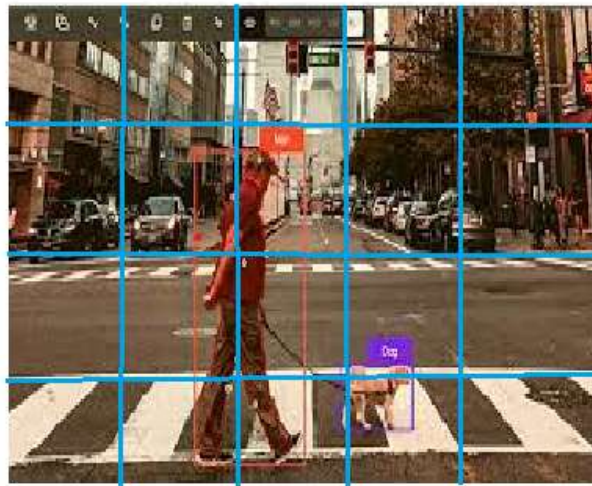
If our image has n objects, then the output vector of size $n * 7$ will likely solve the issue.

Let's say we have an image with two objects.



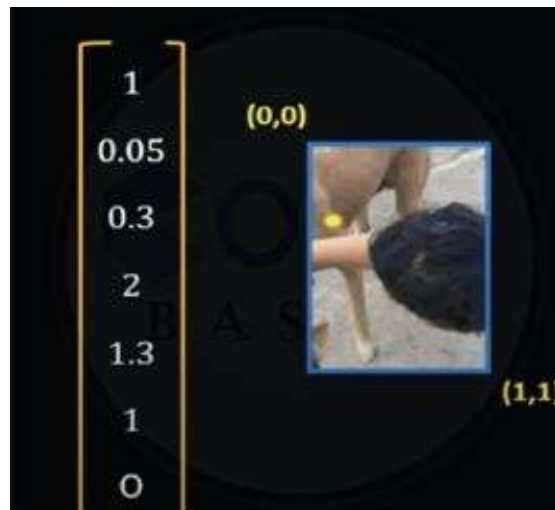
Steps of Working of the Yolo:

Step 1: Divide the image into the grids.



You can divide an image into grids by drawing horizontal and vertical lines to create a series of squares or rectangles. This can be useful for a variety of purposes, such as organizing the elements of the image, making it easier to edit or analyze, or simply to create a visually appealing effect. This can help you to understand the various segments of the image.

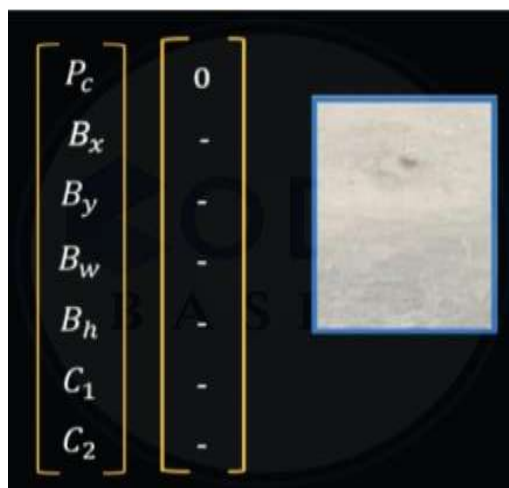
Step 2: Mark the center of each object



It might be helpful to mark the centre of each object in an image for a number of reasons, including object alignment, composition analysis, or just for reference. You may quickly and precisely mark the centre of each object in your image by using the grid or guide tool.

Marking the Centre of each object in an image may be useful for a variety of purposes, such as object alignment, composition analysis, or just as a point of reference. Using the grid or guide tool, you may quickly and precisely indicate the centre of each object in your image.

Step 3: Generates the output vector for each grid formed. For each and every vector we can get the grid and that can give the classification of the image. Grids without any objects will be just marked with empty vectors as below.



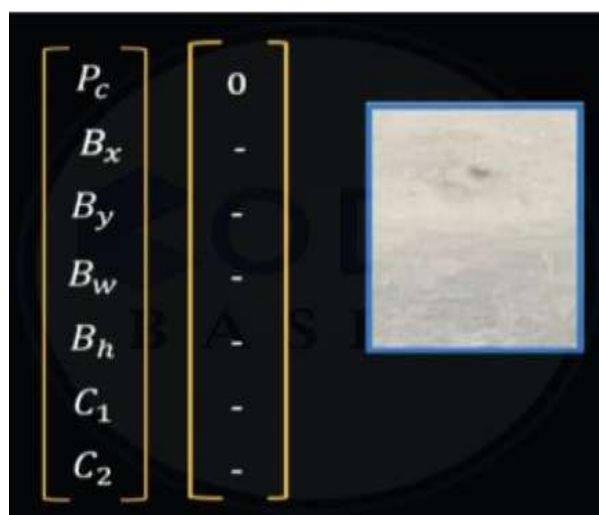
Let's think about the grid below. Here, the grid is classified into a certain class by the model using the object's centre. This grid will be handled as a dog object because its centre is a dog.

This is how YOLO generates output vectors of size 7 for each grid. So, for our image with 4 x 4 grid, we will get 4 x 4 x 7 vectors. This will be fed into a neural net for training.

V. RESULT AND ANALYSIS

The results and analysis of a pedestrian detection project will depend on the specific goals and objectives of the project, as well as the techniques and methods used. In general, a pedestrian detection project may seek to assess the effectiveness of various algorithms or strategies for spotting pedestrians in pictures or videos or to contrast the effectiveness of various methods on various datasets.

The mean average precision is one typical indicator for assessing the effectiveness of a pedestrian detection algorithm (mAP). This statistic assesses how well the system detects and identifies pedestrians in the pictures or videos. The false positive rate, false negative rate, and overall accuracy are additional metrics that can be used to assess how well a pedestrian detection system performs.



In addition to assessing the algorithm's performance, it's crucial to take into account other elements, such as the algorithm's speed and efficiency, robustness to changes in lighting and weather, and capacity to deal with obstacles like occlusions.



Overall, the results and analysis of a pedestrian detection project will provide insights into the strengths and weaknesses of different approaches, and can help guide the development of more effective and reliable pedestrian detection systems.

Model	Accuracy	Precision	F1 Score
MobileNet ssd	50%	61.2%	68%
YoloV3	60%	68.9%	71%
Yolov3tiny	78%	75.5%	77%
YoloV4tiny	96.5	88.8%	89%

Table 1. Analysis of Accuracy, Log-Loss and F1 Score

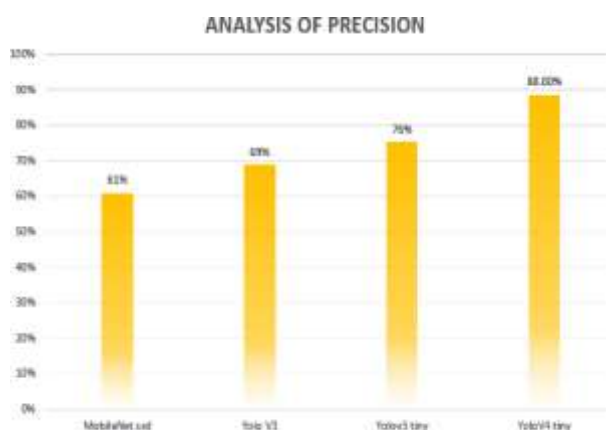


Fig 2 Analysis of Precision

From the above figure 2, it gives a clear picture of various algorithms and their respective Precision values. It is evident that the Log-Loss value is minimum when the model is Mobile Net SSD with a value of 61% only, whereas the maximum value of Log-Loss can be observed when the model is YoloV4 tiny with a value of 88.8% approximately.

The above figure 3, details about the accuracy values when tested by various machine learning algorithms. The accuracy has been the maximum when the model is YoloV4 tiny with a whopping value of 96.5% approximately.

Whereas the minimum value of accuracy when compared with four algorithms is observed when the model is with of 50% approximately. Hence the study clearly mentions that the Logistic Regression algorithm is proved to be the highly optimized algorithm providing the most promising results.

VI. CONCLUSION

Accident Prevention System is one of the most important and effectively addresses the issues that people and animals who cross the road face. YoloV4 is an algorithm that allows us to categorise photos with high precision and a low error rate. It operates well in low light situations and can identify people up to 30 metres away.

FUTURE SCOPE

In order to develop more complex and advanced intelligent transportation systems, it is also possible to combine pedestrian detection systems with other technologies, such as communication networks and location services. For instance, pedestrian detection could be employed to increase the effectiveness and security of traffic flow or to give pedestrians real-time information and direction.

Overall, the future scope of detection is vast and there are many exciting opportunities for further research and development in this area.

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