



## A Deep Neural Network Based Traffic Control System in Intelligent Transportation System with Special Considerations for Emergency Vehicles and traffic density

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### Abstract

This work proposes the development of a deep neural network based traffic control system in intelligent transportation system with special considerations for emergency vehicles and traffic density. This work would ensure that a deep neural network in the form of convolutional neural network is applied in traffic control system so as to ensure that traffic is managed in a more intelligent manner. Here, traffic is assigned to a particular direction based on the traffic density and the emergency situations. A you only look once version 4 model (YOLOV4) was used to identify the cluster of traffic in all the directions on the road. To avoid allocating right of passage to a direction without traffic and allocating very small time of passage to a direction with heavy traffic, the yolov4 model was used to determine the direction with the highest cluster of traffic and a right of passage is given to it. A direction with a right of passage continues until another direction becomes the highest cluster of traffic or an emergency vehicle appears in another direction. The system allows a pedestrian passage of 20 seconds after each transition. In this study, 200 images of normal traffic were captured by cameras and 50 images of traffic with emergency vehicles like ambulances, fire trucks, military and police vehicles were equally captured by cameras. Then, 2000 images of normal traffic and 100 images of traffic with emergency vehicles were also downloaded from the internet. Hence, total of 2350 traffic images were preprocessed using python language to form the training data set that was used to train the deep neural network ( yolov4) model in google colab platform using python language programming. The trained deep neural network was tested for classification of traffic into normal and emergency traffic using 700 traffic images and it was able to show precision of 96%, accuracy of 97%, recall of 0.96 and F1score of 0.96. This model would reduce the wastage of traffic time in wrong direction as common with the traditional traffic control that even assigns traffic passage to a direction without any traffic on it. Hence, it would assign traffic passage based on the traffic density and emergencies on the road.

**Keywords:** Intelligent Transportation System; Deep Neural Network; YOLOv4; Traffic Density Management; Emergency Vehicle Detection

## 1.0 Introduction

Traffic signal control and management at road intersections is a difficult task in the transportation system where the safety of pedestrians, drivers, vehicles and steady flow of traffic must be upheld at all times. Intersections are the points at which two or more roads meet. At crossroads, people, automobiles, and bicycles change directions at intersections. Because of the enormous number of vehicles commuting from one location to another, intersections serve as an obstacle to resist smooth traffic flow inside urban and developed areas. This causes traffic disruption, congestion, and inadequate traffic control and management [1, 2, 3, and 4]. The intersection delay has an impact on the signal control logic as well as road users' travel efficiency [5, 6, and 7]. According to one study, fixed traffic signal delays account for more than 10% of all traffic delays worldwide. At major U.S. highway crossings, traffic delays totaled over 295 million hours [8, 9, and 10]. As a result, the exact estimations of time-dependent delays are very required at urban roadway intersections for traffic signal control and management. Intelligent Transportation System (ITS) has been very essential in modern traffic management, offering improved safety, flow, and overall transport experience by way of innovative solutions. These systems employ real-time traffic signal recognition, which is key in controlling traffic and managing road safety and vehicle tracking. Real-time traffic signal recognition optimizes signal management. Prior to now, traffic control has evolved from manual to automatic and now intelligent control system. Intelligent Transportation Systems (ITS) address the challenging problem of effective traffic control and management at intersections. It is important to have a good mix of safe and effective traffic control at intersections so that most cars can pass while still keeping people safe [11, 12]. Currently, traffic-light signaling is utilized to govern traffic at critical junctions by distributing the same green light timings to all routes [13, 14] which is ineffective since it does not consider traffic density and emergency traffic. The complex architecture of traffic systems does not coordinate the timings of traffic signals with average daily road traffic, resulting in intersection congestion. Therefore, the city's transportation system is in need of innovative solutions because the urban infrastructure changes will take years, and may not even be feasible at all. The optimization of traffic signal time (TST) is one of the most effective methods for reducing congestion at junctions and increasing traffic flow throughout the metropolitan network. Numerous techniques to improve the TST have already been investigated by researchers. The issue of TST or traffic system control (TSC) settings has been the subject of a number of high-quality reviews [15, 16]. There are two survey articles that were published in 2015 that cover a wide range of methods used in this field up until 2022 [17]. Hence, there is need for this research which would assign green light of passage based on the traffic density and emergency traffic on the roads.

## 2.0 Methodology

### 2.1 Data collection

The data used in this study were traffic images captured on five different road intersections in Enugu, capital of Enugu state in Nigeria and the traffic images downloaded from the internet. A high definition camera in plate 2.1 was used to capture the traffic images. In the course of this research study, a high definition camera of plate 2.1 was used to capture 200 images of normal traffic and 50 images of traffic with emergency vehicles like ambulances, fire trucks, military and police vehicles at crossroads at Agbani road, Zik's avenue, Nenwe street, New haven, Bisalla road and Ogui road all in the capital city of Enugu, Nigeria. Some of the captured traffics are shown in plates 2.2 and 2.3. Also, 2000 images of normal traffic and 100 images of traffic with emergency vehicles were also downloaded from the internet.



**Plate 2.1: A digital camera for capturing of traffic images**



**Plate 2.2: A normal traffic image captured along Agbani road, Enugu, Nigeria.**



**Plate 2.3: A traffic image captured with emergency vehicles along New haven, Enugu, Nigeria.**

## **2.2 Preprocessing of captured traffic images to form training datasets**

Total of 2350 traffic images from both the roads and internet were preprocessed using python language to form the training data set that was used to train the deep neural network (yolov4) model in google colab platform using python language programming as shown in figure 2.1.

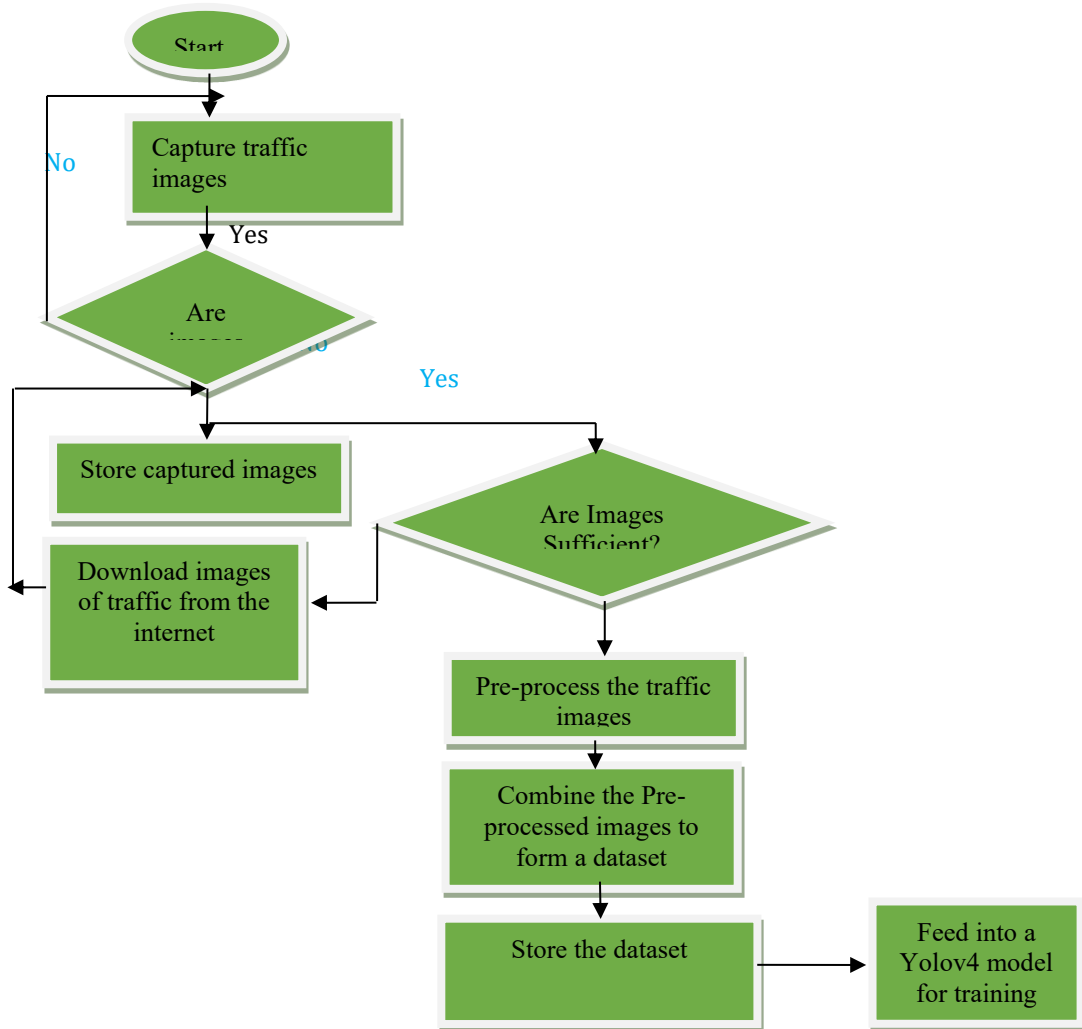


Figure 2.1: Flowchart for the preprocessing of captured traffic images to form training data sets.

### 2.3 You Only Look Once (YOLOV4) Model

It is a real time image detection model that uses the convolutional neural network architecture in its operation. A YOLOV4 just as other YOLO models detect image clusters by dividing the video frames into smaller boxes and counts the number of boxes with images in it and use that for its decision. This yolov4 is trained in the subsequent section so as to be able to identify normal traffic images and emergency traffic images and use it together with the traffic density to make intelligent decisions in traffic control and management system [18, 19, 20]. YOLOV4 is a one stage detector architecture comprising of four parts as shown in figure 2.2.

- Input part- It is the set of traffic image data we want to detect
- Backbone – It is responsible for extracting the features from the different traffic images. In object detection, multiple bounding boxes need to be drawn around images along with classification, so the feature layers of the convolutional backbone need to be mixed and held up in light of one another.
- Neck - The combination of backbone feature layers happens here.
- Head (Dense prediction) – It is where the real time object detection happens.

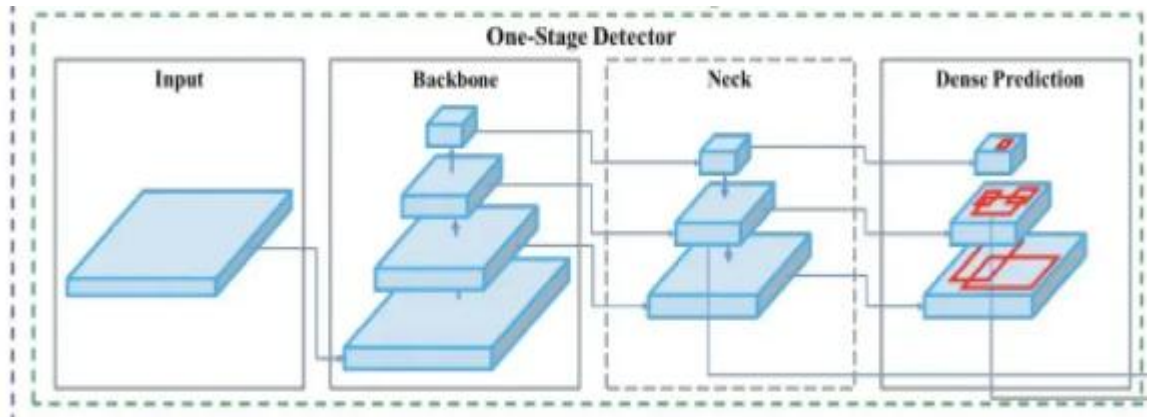


Figure 2.2: A You Only Look Once (YOLOV4) Model for traffic images detection

#### 2.4 Training of the YOLOV4 Model with training datasets

The YOLOV4 model in figure 2.2 was trained with the dataset developed in figure 2.1 by preprocessing 2350 traffic images captured on the selected roads in Enugu, Nigeria and from the internet. The training was done in google colab platform with 50 epochs and back propagation training method was employed. The result will be shown at the subsequent session[21, 22 and 23].

#### 2.5 Development of Traffic Algorithm that controls traffic using the YOLOV4 model classification of traffic images.

The algorithm for the traffic control and management is as follows and deployed in real life using flow tensor lite:

- Step 1: Start cameras and traffic lights
- Step 2: Capture images
- Step 3: Send captured images to trained YOLOV4 Model
- Step 4: Are captured images traffic?
  - No; Go back to Step 2
  - Yes; Go to Step 5
- Step 5: Is any of the route's traffic with emergency images?
  - Yes; Go to step 6
  - No; Go to step 7
- Step 6: Give right of passage (Green light) to the route with emergency image
- Step 7: Give right of passage (Green light) to the route with the highest traffic density
- Step 8: Give 15 seconds for Pedestrian crossing after each route passage
- Step 9: Are two or more routes of the same traffic density?
  - No; Go back to Step 7
  - Yes; Go to Step 10
- Step 10: Give right of passage (Green light) to the route that has the highest delay time.
- Step 11: Go back to Step 7. The flow of figure 2.3 is derived from this algorithm.

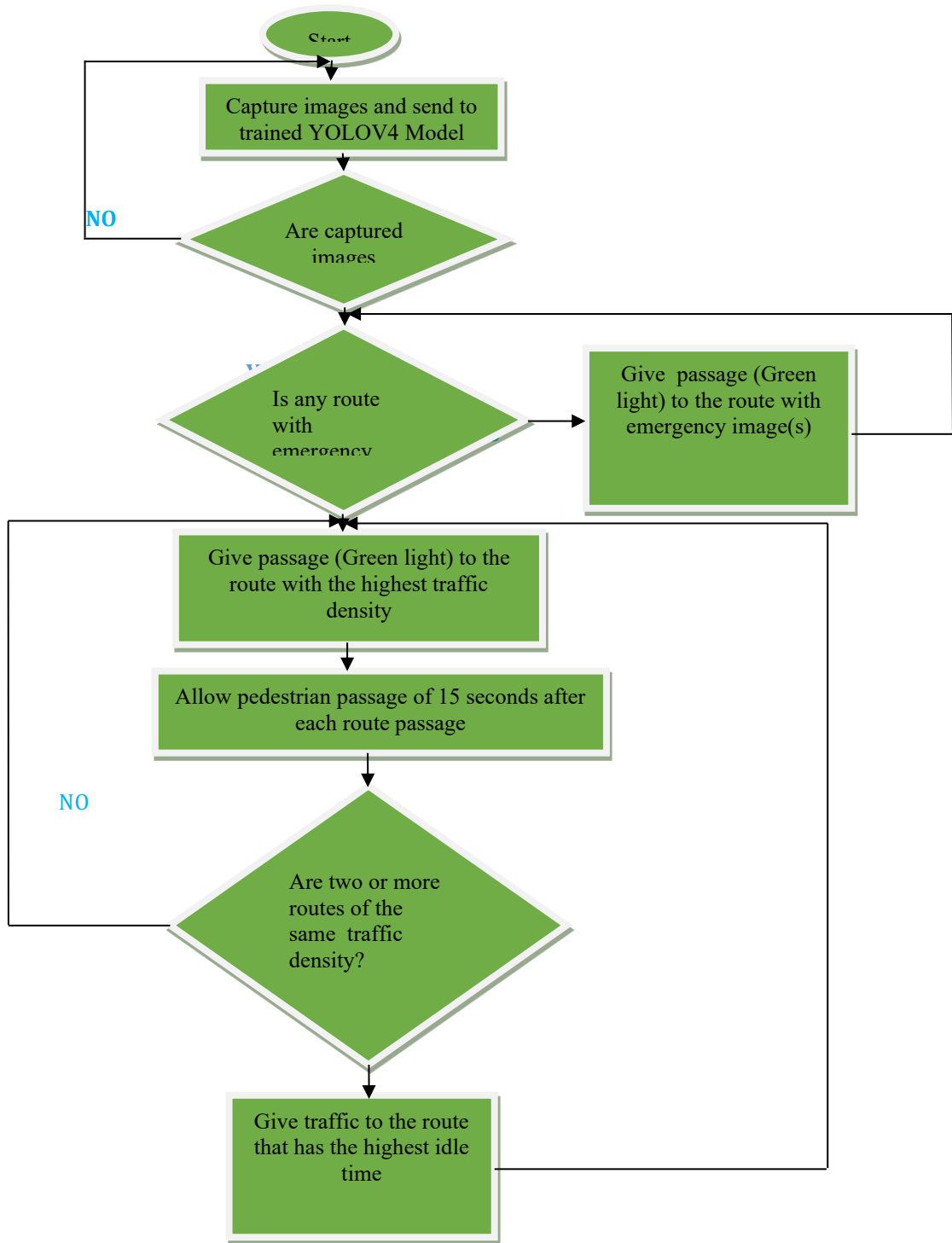


Figure 2.3: Flowchart of the developed traffic algorithm

### 3.0 Results and Discussions

The developed intelligent traffic control system based on YOLOV4 model was trained in the google colab platform using 2350 traffic images and also used for prediction of 700 traffic images into normal and emergency traffic images in google colab platform.

#### 3.1 Training Result of the YOLOV4 Model for Traffic Image detection

The YOLOV4 model was trained in google colab platform with 2350 traffic images with epoch of 50 and back propagation training method with results as shown in figure 3.1, table 3.1 and table 3.2.

Table 3.1: Result of training and validation accuracies of the YOLOV4 model training with epoch = 50.

Epoch	Training Accuracy	Validation Accuracy
1	0.05432	0.3451
2	0.05510	0.4002
3	0.1034	0.4123
4	0.2023	0.4543
5	0.3456	0.4675
6	0.6103	0.6756
7	0.7367	0.7873
8	0.7567	0.7023
9	0.7789	0.7876
10	0.8000	0.8000
11	0.8123	0.8124
12	0.8356	0.8435
13	0.8445	0.8345
14	0.8466	0.8456
15	0.8590	0.8590
16	0.8605	0.8690
17	0.8745	0.8745
18	0.8789	0.8786
19	0.8865	0.8967
20	0.8901	0.8823
21	0.8923	0.8860
22	0.8938	0.8445
23	0.8941	0.8897
24	0.8958	0.8917
25	0.8969	0.8978
26	0.8968	0.8986
27	0.8976	0.8988
28	0.8980	0.8990
29	0.8988	0.9001
30	0.8990	0.8999
31	0.8997	0.9007

32	0.9070	0.9010
33	0.9098	0.9050
34	0.9100	0.9099
35	0.9143	0.9108
36	0.9156	0.9213
37	0.9168	0.9148
38	0.9176	0.9157
39	0.9188	0.9179
40	0.9198	0.9189
41	0.9245	0.9345
42	0.9134	0.8976
43	0.9345	0.9356
44	0.9455	0.8123
45	0.9567	0.9245
46	0.9472	0.9398
47	0.9564	0.9453
48	0.9604	0.9567
49	0.9698	0.9668
50	0.9678	0.9678

Table 3.2: Result of training and validation losses of the YOLOV4 model training with epoch = 50.

Epoch	Training loss	Validation loss
1	2.002	2.040
2	1.8756	1.8890
3	1.7508	1.7500
4	1.6780	1.6789
5	1.5702	1.4567
6	1.2457	1.0245
7	0.9760	0.7873
8	0.7567	0.7623
9	0.7789	0.7876
10	0.6000	0.6000
11	0.5123	0.5912
12	0.5056	0.4835
13	0.4445	0.4745
14	0.4266	0.4056
15	0.4190	0.4190
16	0.3905	0.3990
17	0.3745	0.3745
18	0.3489	0.3486
19	0.3265	0.3167
20	0.3001	0.2523

21	0.2923	0.2566
22	0.2838	0.2445
23	0.2741	0.2497
24	0.2708	0.5017
25	0.2669	0.4378
26	0.2658	0.2586
27	0.2607	0.2488
28	0.2605	0.2470
29	0.2508	0.3008
30	0.2500	0.3129
31	0.2501	0.2845
32	0.2498	0.2346
33	0.2487	0.2467
34	0.2457	0.2456
35	0.2461	0.3456
36	0.2450	0.3657
37	0.2434	0.2976
38	0.2430	0.2567
39	0.2423	0.2548
40	0.2410	0.2507
41	0.2445	0.3345
42	0.2403	0.4876
43	0.2345	0.3356
44	0.2255	0.2523
45	0.2298	0.2245
46	0.2176	0.2398
47	0.2164	0.2453
48	0.2004	0.2367
49	0.1998	0.1968
50	0.1878	0.1878

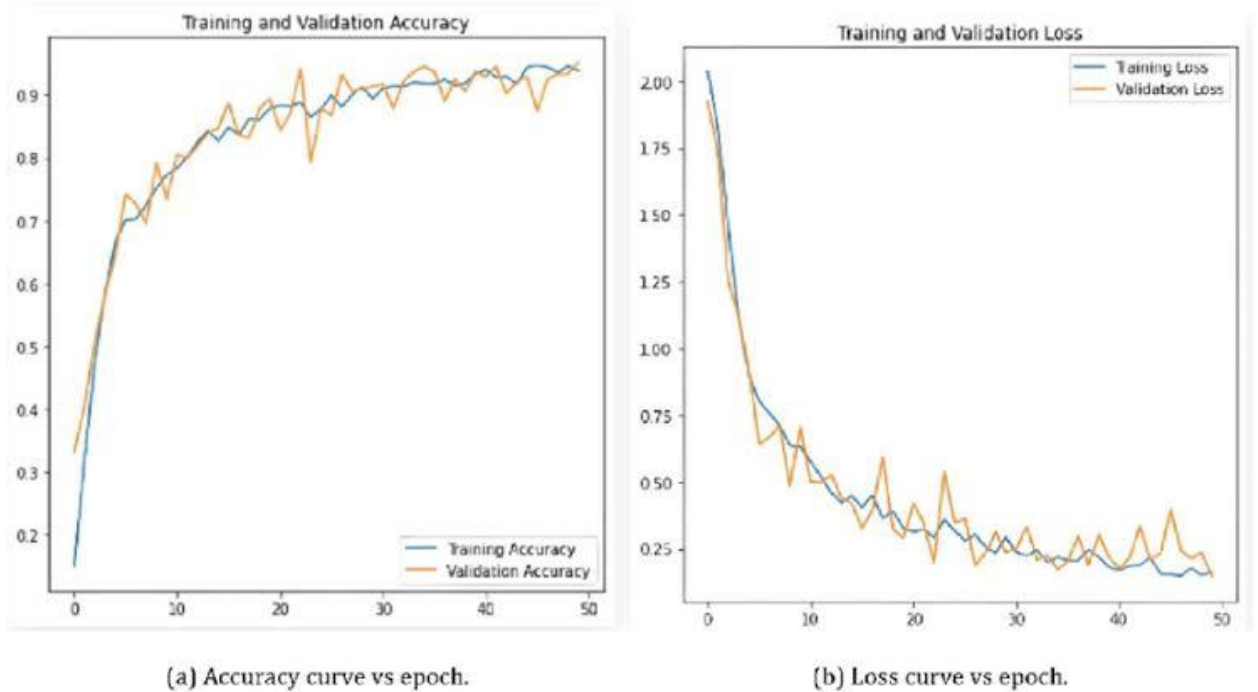


Figure 3.1: Training and validation accuracies and losses for epoch =50

Figure 3.1 and tables 3.1 and 3.2 showed the training and validation accuracies and losses of the training of the YOLOV4 model for traffic images detection with very high training and validation accuracies of 96% at the 50 epoch and also very low losses for the training and validation of 18% at the epoch= 50. Hence, the model is properly trained to detect the traffic images and classify them into normal and emergency traffic images.

### 3.2 Classification of Traffic Images into Normal and Emergency Images by the YOLOV4 Model in Google Colab

Figure 3.2 showed the classification of emergency traffic image by the trained YOLOV4 model in google colab platform. Also, another image was fed to the trained YOLOV4 model and it classified it correctly as normal traffic image as shown in figure 3.3.



Figure 3.2: Classification of emergency traffic images by the trained YOLOV4 model

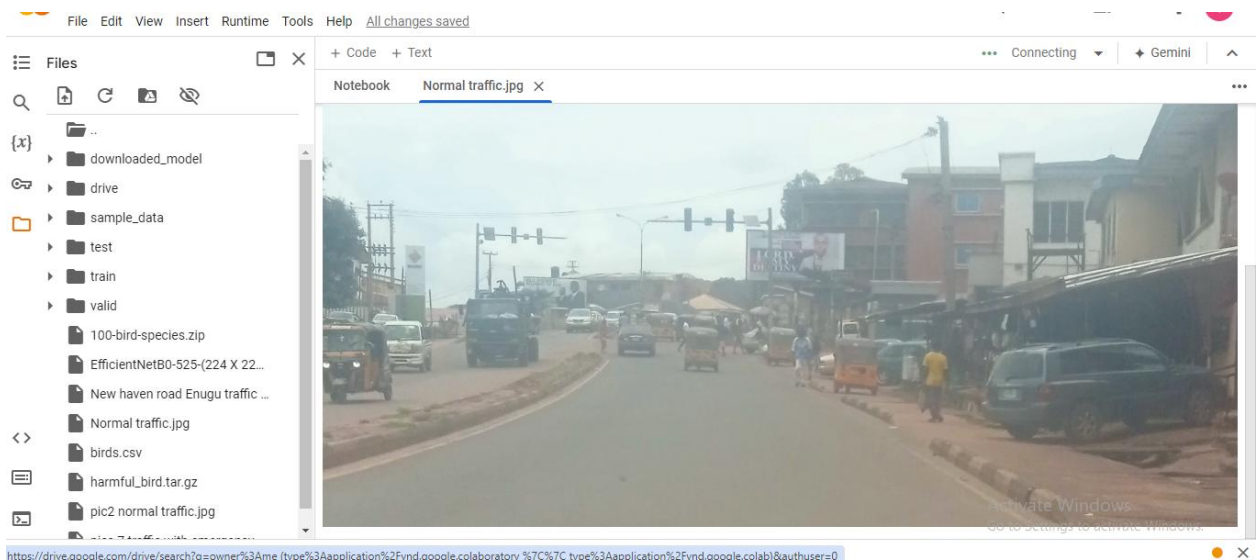
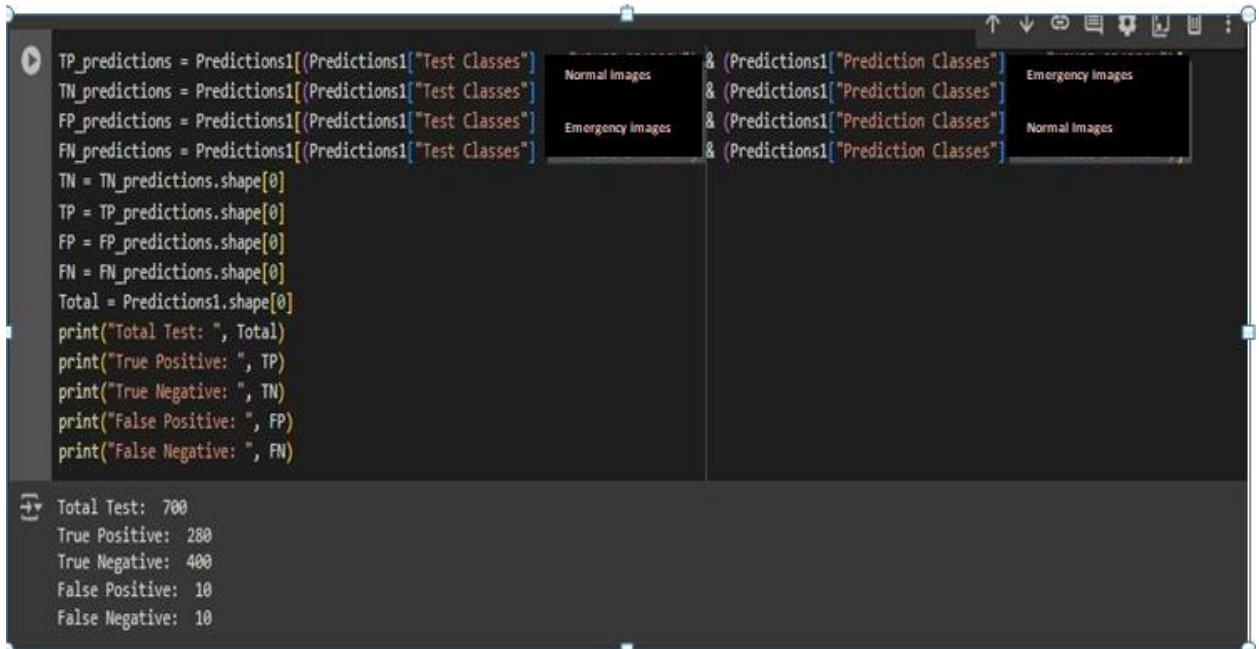


Figure 3.3: Classification of normal traffic images by the trained YOLOV4 model

### 3.3 Result of the Model Prediction with 700 Traffic Images

Figure 3.4 showed the result of the traffic image predictions of the trained YOLOV4 model in google colab platform. Out of the 700 traffic images fed to the trained YOLOV4 model, it was able to classify properly 700 normal traffic images and 280 emergency traffic images. However, it incorrectly predicted 10 normal traffic images and 10 emergency traffic images. Using the True positive = 400, True Negative = 280, False Positive = 10 and False Negative = 10, the system returned accuracy of 97%, Precision of 96%, Recall of 0.965 and F1 score of 0.965.



```
TP_predictions = Predictions1[(Predictions1["Test Classes"]
TN_predictions = Predictions1[(Predictions1["Test Classes"]
FP_predictions = Predictions1[(Predictions1["Test Classes"]
FN_predictions = Predictions1[(Predictions1["Test Classes"]
TN = TN_predictions.shape[0]
TP = TP_predictions.shape[0]
FP = FP_predictions.shape[0]
FN = FN_predictions.shape[0]
Total = Predictions1.shape[0]
print("Total Test: ", Total)
print("True Positive: ", TP)
print("True Negative: ", TN)
print("False Positive: ", FP)
print("False Negative: ", FN)
```

```
Total Test: 700
True Positive: 280
True Negative: 400
False Positive: 10
False Negative: 10
```

Figure 3.4: Prediction result of the trained YOLOV4 model using 700 traffic images

#### 4.0 Conclusion

Traffic control and management system has evolved over the years from the manual through automatic to the present intelligent control system. This research study has shown that with deep learning neural network based system that the traffic system can be better managed and controlled based on emergency services and traffic density for optimal performance. The trained YOLOV4 model used in this research was trained in google colab platform to predict 700 different traffic images with accuracy of 97%, precision of 96%, recall of 0.965 and F1 score of 0.965. Hence, if this model is deployed in urban areas like Enugu in Nigeria where the research was carried out, it would ensure efficient and effective utilization of traffic right of passage (green light) based on the traffic density and delivery of essential emergency services like ambulance, fire truck, police or military services. Above all, it will eliminate the incidence of giving a right of passage to routes without traffic which is common with most automatic control traffic system.

#### Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship and publication of this article.

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