**System Description and Implementation**

The YOLOv5 deep learning model forms the core of the proposed system, designed for detecting and classifying vehicles. The model has been trained on a dataset of 7,500 images, collected using a suitable camera capturing the diverse array of vehicles on the streets of Iraq. These images have been pre-classified into five categories: personal cars, taxi cars, minibus cars, trucks, and tuk-tuks.

Google Colaboratory (<https://colab.research.google.com/>) provides the platform for the training process. After 100 epochs, the model achieves an Odds Ratio mAP of 0.924, indicative of the model's high accuracy in identifying and categorizing vehicles.

The YOLOv5 network architecture is composed of three primary components:

1. Backbone: The CSPDarknet, which is tasked with the initial extraction of features from the input data.
2. Neck: The PANet, which performs the fusion of the extracted features.
3. Head: The YOLO Layer, which generates the output results of the detection process, including class, score, location, and size of the detected vehicles.

**Results and Discussion**

The proposed system, based on YOLOv5, demonstrates excellent results in the field of vehicle detection and classification. It accurately identifies and classifies different types of vehicles with an impressive mAP score of 0.924 after 100 epochs of training.

The system outperforms previous models in the literature. For example, the YOLOv4-based system proposed by V Sowmya and R Radha achieved an accuracy of 96.54 percent (mAP) for detection, but the dataset consisted only of 3,500 images of buses and trucks.

The proposed system offers an efficient solution for vehicle detection and classification, with potential applications in traffic monitoring and autonomous driving.

**Efficiency Metrics of the Proposed System**

The proposed system's efficiency is demonstrated in Table 2 below:

| **Classes** | **TP** | **FP** | **FN** | **F1** | **Recall** | **Precision** |
| --- | --- | --- | --- | --- | --- | --- |
| CAR-F | 0.92 | 0.13 | 0.08 | 90 | 92.000 | 87.619 |
| CAR-R | 0.9 | 0.9 | 0.09 | 91 | 90.909 | 90.909 |
| CAR-S | 0.9 | 0.1 | 0.1 | 90 | 90.000 | 90.000 |
| TAXI-F | 0.98 | 0.08 | 0 | 96 | 100.000 | 92.453 |
| TAXI-R | 0.97 | 0.07 | 0.01 | 96 | 98.980 | 93.269 |
| TAXI-S | 0.93 | 0.06 | 0.02 | 96 | 97.895 | 93.939 |
| MINIBUS-F | 0.93 | 0.11 | 0.06 | 92 | 93.939 | 89.423 |
| MINIBUS-R | 0.94 | 0.06 | 0.05 | 94 | 94.949 | 94.000 |
| MINIBUS-S | 0.9 | 0.06 | 0.07 | 93 | 92.784 | 93.750 |
| TRUCK | 0.93 | 0.11 | 0.03 | 93 | 96.875 | 89.423 |
| TUK-TUK | 0.93 | 0.13 | 0.06 | 91 | 93.939 | 87.736 |

**Conclusion**

Determining vehicle direction yields several benefits, particularly for people with special needs. This includes determining the direction of travel and identifying vehicles moving in the wrong direction. Such technology is particularly useful for visually impaired individuals, aiding them in understanding traffic direction.

The proposed system highlights the utility of the YOLO network in accurately detecting objects. This reliability bodes well for real-time systems that require a high degree of accuracy and fast response times.