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DYNAMIC TRAFFIC MONITORING USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

This initiative centers on the vital task of estimating traffic density, a crucial element in urban and traffic management endeavors. Its primary focus is on accurately tallying vehicles within specified zones per frame. The data gathered serves as a cornerstone for evaluating traffic density, pinpointing peak traffic times, and identifying congested areas. The ultimate goal is to develop a comprehensive toolkit that provides detailed understandings of traffic flow and trends. Through this endeavor, the intention is to substantially bolster traffic management strategies and facilitate more informed urban planning efforts.

Keywords: YOLOv8, Traffic Density, Real Time Monitoring, Object Detection.

I. INTRODUCTION

As urban areas grapple with escalating traffic volumes, the demand for automated transportation solutions becomes increasingly imperative. The rapid proliferation of vehicles poses a significant hurdle in sustaining an effective transportation network. To effectively manage this challenge, automated vehicle counting systems emerge as indispensable tools for intelligent surveillance of transportation systems, facilitating real-time monitoring of traffic dynamics.

II. METHODOLOGY

2.1 Data Preparation

The dataset employed in this project comprises images capturing vehicular activity sourced from diverse channels. These images underwent annotation processes, wherein bounding boxes delineating the contours of vehicles were meticulously marked, thereby facilitating the training of the model. To optimize dataset integrity and enhance model efficiency, data preprocessing methodologies were applied.

Fig 1: Model Detecting and labelling Vehicles

3.2 Model Training

To tailor the YOLOv8 model specifically for the task of vehicle detection within the project's context, transfer learning methodologies were judiciously applied. This involved retraining the model on the custom dataset curated for the project. By harnessing transfer learning, the model underwent fine-tuning processes that honed

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its capabilities to discern and localize vehicles withheightened precision and reliability.

Through this strategic fusion of pre-existing knowledge and targeted refinement, the YOLOv8model emerged as an adept tool for detecting vehicles within the project's domain. Its utilization not only expedited the development process but also yielded a robust and proficient solution capable of meeting the project's objectives with exceptional performance.

3.3 Model Evaluation

Following the training phase, the efficacy of the trained model was rigorously assessed through an evaluation protocol employing a distinct set of validation images. This separation of data ensured an unbiased appraisal of the model's performance, free from the influence of the training dataset.

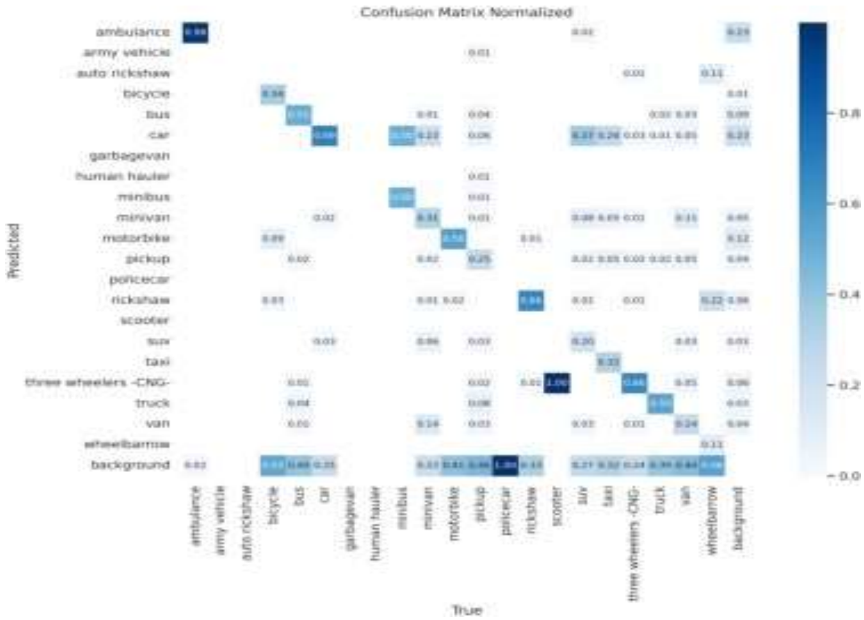

Fig 2: Correlation between features

The heatmap provides a visual representation of the relationships between various features extracted from the URLs. For instance, a dark red square might indicate a strong negative correlation, while a bright lite orange square might show a strong positive correlation. These relationships can provide valuable insights into how features work together.

We use classification metrics such as accuracy, precision, recall, and F1 score to evaluate the performance of each machine learning model. These metrics provide an overall measure of the model's ability to accurately identify phishing URLs.

III. MODELING AND ANALYSIS

Performance Metrics:

- **Accuracy:** This metric reflects the overall proportion of correct predictions made by the model. It tells us how often the model correctly classifies a URL as phishing or legitimate.
- **Precision:** Precision focuses specifically on the model's ability to accurately identify phishing URLs. It calculates the percentage of URLs flagged as phishing by the model thatare actually malicious.
- **Recall (Sensitivity):** This metric looks at the flip side of precision. It tells us what percentage of actual phishing URLs the model successfully identified. A high recall indicates the model catches most phishing attempts.
- **F1-Score:** This metric strikes a balance between precision and recall, providing a single measure that considers both.
- **Validation:** In machine learning, training is the iterative process of adjusting a model's parameters using labeled data to minimize prediction errors, while loss quantifies the disparity between predicted and actual outcomes, guiding the optimization process towardsbetter performance.

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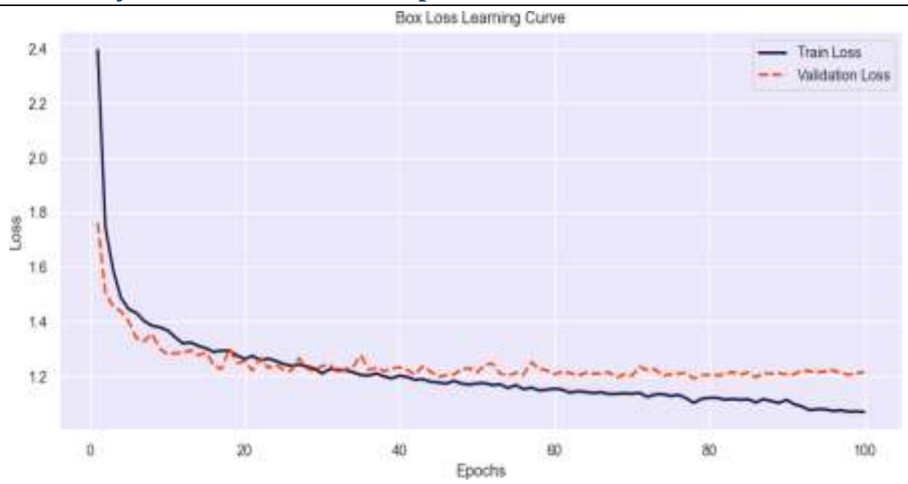

Fig 3:

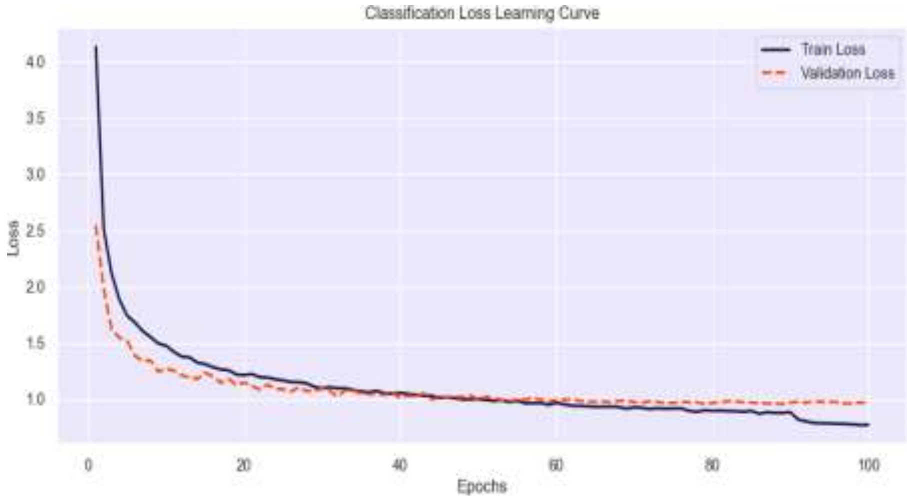

Fig 4:

IV. RESULTS AND DISCUSSION

Aside from its primary function of vehicle detection, the system was engineered to conductin-depth analysis of traffic density within a sample video. This multifaceted task encompassed the detection of vehicles across sequential video frames and the subsequent estimation of traffic intensity within distinct lanes. By meticulously scrutinizing these dynamics, the system yielded invaluable insights into prevailing traffic patterns and levels of congestion, thereby furnishing stakeholders with actionable intelligence for enhancing traffic management strategies and optimizing urban mobility.

Table 1: Results of Prediction

Metric	Value
metrics/precision(B)	0.856
metrics/recall(B)	0.819
metrics/mAP50(B)	0.768
metrics/mAP50-95(B)	0.596
fitness	0.713

V. CONCLUSION

The outcomes comprise annotated images showcasing detected objects, along with dataset details including image counts and dimensions. Training progress is depicted through learning curves, while validation metrics offer quantitative evaluations of model performance. Visual representations of results from the validation set offer qualitative insights, while a traffic density analysis demonstrates vehicle counts and congestion levels. Furthermore, the exported model enables seamless deployment and applications.

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