

# VEDA-Net: A Lightweight CNN Framework with Differential Attention and Edge-Aware Fusion for Real-Time Vehicle Detection

Hemant Kumar 

Department of Computer Science & Engineering,  
Chhatrapati Shahu Ji Maharaj University, Kanpur, India

ROR <https://ror.org/040qxz868>

 [hemant.kumar2k13@gmail.com](mailto:hemant.kumar2k13@gmail.com)

<https://orcid.org/0000-0001-5719-1889>

Pushpa Mamoria 

Department of Computer Application,  
Chhatrapati Shahu Ji Maharaj University, Kanpur, India

ROR <https://ror.org/040qxz868>

 [pushpamamoria@csimu.ac.in](mailto:pushpamamoria@csimu.ac.in)

<https://orcid.org/0000-0002-5748-7302>



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**Abstract:** Vehicle detection with a camera-based vision sensor in real time settings are critical for ensuring both the dependability and safety of AVS. In this paper we propose vehicle detection architecture using differential attention mechanisms and edge aware features (VEDA-Net). This is a lightweight CNN model which uses the Edge-Aware Feature Extraction (EAFE) technique to extract edge aware features from images. Dual Path Fusion (DPF) for fusing dual paths of information; and Differential Attention Module (DAM) to enhance the detection robustness in complex traffic environment. Additionally, VEDA-Net has a Compact Head for Detection (CHD) module that outputs bounding box and class probability through an anchor free regression method. Due to its low latency characteristics, VEDA-Net is suitable for use as an edge-based Autonomous vehicle system (AVS) perception module. On the COCO traffic dataset, VEDA-Net achieved an accuracy rate of 81%, a recall rate of 79%; and mAP@0.5 of 94%. Compared to YOLOV5s; Efficient Det-D0; and Tiny-YOLOv4, VEDA-Net's performance increased by 12%; 6%; and 16% respectively. Averaging over 500 epochs at a frame rate of 30 FPS, the average inference latency was 21.28ms. Based on qualitative results, the model demonstrated high levels of robustness under various levels of occlusions; different lighting conditions; and real-world clutter. By focusing on structural feature extraction, and selectively attending to consistent spatial regions in vehicles, VEDA-Net provides high detection robustness. As such, due to its modular and compact nature, VEDA-Net will be suitable for use as a detection module within edge-based AVS applications that require rapid, accurate, and light-weight perception modules.

**Keywords:** Autonomous vehicle system, Convolutional Neural Network, vehicle detection, VEDA-Net, deep learning, vision Sensor.

## I. INTRODUCTION

Vehicle detection plays a vital part in creating AVS and intelligent driving platforms where real time environmental perception is key to both safe navigation and effective traffic management [1], [2]. CNN's object detection has improved dramatically but still faces many challenges in uncontrolled environments with occlusions, dynamic lighting and complex backgrounds [3-5]. The most common object detection frameworks like YOLO and Single Shot MultiBox Detector (SSD), primarily rely on high-level semantic features extracted from RGB Images. This reliance on colour and texture information limits its ability to clearly localize boundaries when necessary. By using edge-based features, we can provide stronger localization cues, which would help the model better discriminate vehicles from cluttered surroundings [15-18]. To address these challenges, we propose VEDA-Net, a novel and lightweight CNN-based framework designed for enhanced vehicle detection under constrained computational settings. VEDA-Net comprises four key components: an EAFE module that integrates edge-derived cues with standard RGB inputs, a DPF mechanism that processes and adaptively merges parallel feature streams, a DAM module that emphasizes meaningful variations between features to guide the detection process more precisely, and a CHD module that create bounding-boxes and predict class scores

without predefined anchors. VEDA-Net is optimized for efficiency and can operate effectively on resource-constrained platforms having embedded GPU such as Google Colab. The key contributions of this work are summarized below

- Input traffic images are processed through the EAFE module to emphasize boundary information. These features are then fused using the DPF module, followed by refinement using the DAM module to focus on contextually important regions.
- The refined features are passed into a lightweight CHD module, designed for efficient and accurate object localization. CHD enables fast and accurate object localization through an efficient, anchor-free detection head.
- The proposed VEDA-Net is validated on the COCO Traffic dataset. Detection performance is measured using mAP@0.5, precision, and recall, and compared with baseline models like MobileNet-SSD, YOLOv5s, EfficientDet-D0, Tiny-YOLOv4 to justify the effectiveness of each module. Website.

## II. RELATED WORK

### A. Attention and Fusion based Approaches

Feature representation is currently one of the most critical aspects of enhancing object detection performance, particularly in very complex scenes. The use of attention mechanisms will allow networks to focus on the relevant spatial and channel-based characteristics that are most important to achieve higher detection accuracy. A CNN-Transformer based architecture was developed by Wang et al. [6], which combined global context learning capabilities with those for local texture preservation within urban scene segmentation. Dang et al. [7] demonstrated the utility of incorporating an attention mechanism into CNNs to enable the network to learn both local features and global contextual dependencies used for remote sensing image segmentation. In another study, Gao et al. [8] suggested a BSEFNet architecture, which uses self-attentive modules to fuse salient object features with edge features, improving boundary accuracy. While, Liu et al. [9] proposed a multi-scale attention and boundary-aware network specifically designed for military camouflaged object detection from UAV imagery, addressing the unique challenges of complex backgrounds and high texture similarity in military scenarios.

### B. Edge-Aware and Structure-Enhanced Approaches

Attention-enhanced variants such as CBAM-YOLO improve focus but often ignore edge cues. Edge-aware models exist but are mostly limited to segmentation. Zhang et al. [10] proposed an Edge-Guided and Differential Attention Network called EGD-Net for detecting defects; this method begins with extracting multi-scale contexts and edge map information from the images. The multi-scale contextual and edge map information are then combined in an edge-fusion module. Finally, a top-down DAM module is used to highlight defects by emphasizing the defective areas of the images while suppressing the background clutter. Wang et al. [11] developed an attention-based and multimodal fusion strategies to enhance RGB-T semantic segmentation. Now, fusion branch utilizes channel and spatial attention to combine modalities, and an edge-aware refinement module to align boundaries across RGB and thermal inputs. Similarly, Mukisa et al. [12] showed how the use of CNNs and transformers in deep learning models could be used to improve the extraction of contextual features for cardiac MRI segmentation. In summary, all discussed approaches to object segmentation have focused on either attention-based context modelling (BANet, MFAFNet, BSEFNet), or have used edge information for boundary refinement (EGD-Net, Edge Aware Fusion Networks), but have generally treated each of these separately. VEDA-Net addresses this limitation by combining edge-aware input having differential attention within a single fusion block, achieving both precise boundary detection and contextual awareness.

## III. METHODOLOGY

### A. Overview of VEDA-Net

VEDA-Net is a lightweight, purpose-built convolutional architecture designed for efficient vehicle detection in real-world settings, particularly under constraints such as low-light visibility, object occlusion, and limited computational resources. The architecture includes four primary components. The first one, EAFE module that is based on sobel-based edge information and RGB image data. It generates the detailed spatial information. The edges are used to enhance the details at an earlier stage in the architecture, resulting in improved sensitivity for object contours. The second one, DPF module simply concatenating multi-modal features as most other methods [7], [11] have done earlier work which processes both RGB and edge features separately using parallel convolutional pathways. Then DPF utilizes a gated fusion mechanism with learnable weights to merge those two feature streams together, enabling the network to decide how much weight to assign each stream. Therefore, the network can select the best possible cue for the task of localizing texture-based vehicles. And third is both DAM and CHD are also designed similar to their predecessors in [10], [14]. DAM operates on top of the fused RGB-edge representation. It is designed to identify feature variation between RGB and edge representations for localizing vehicles. Following [14], CHD is a lightweight anchor-free detection head; it outputs bounding box coordinates and objectness scores directly from fused RGB or edge feature space. Finally, post-processing Non-Maximum Suppression (NMS) is applied to eliminate duplicate detections. The complete model workflow is illustrated in Fig. 1, while the internal working of these modules is illustrated in Fig. 2.

### B. Network Architecture and Specifications

Vehicles can be classified and localized with good accuracy in different environments. However, this requires a strong ability for extracting features that are able to provide an accurate description of objects despite being occluded, or having poor lighting etc. A new low resource design of a network, called VEDA-Net was developed in order to provide an improved solution to this problem by providing two paths of spatial-edge and contextual cues. In designing the VEDA-Net, it was determined through experimentation that using a 3×3 convolution kernels would produce a suitable trade-off between feature quality and computational cost. A detailed listing of all the configurable elements of each of the layers used within the VEDA-Net is shown in Table 1.

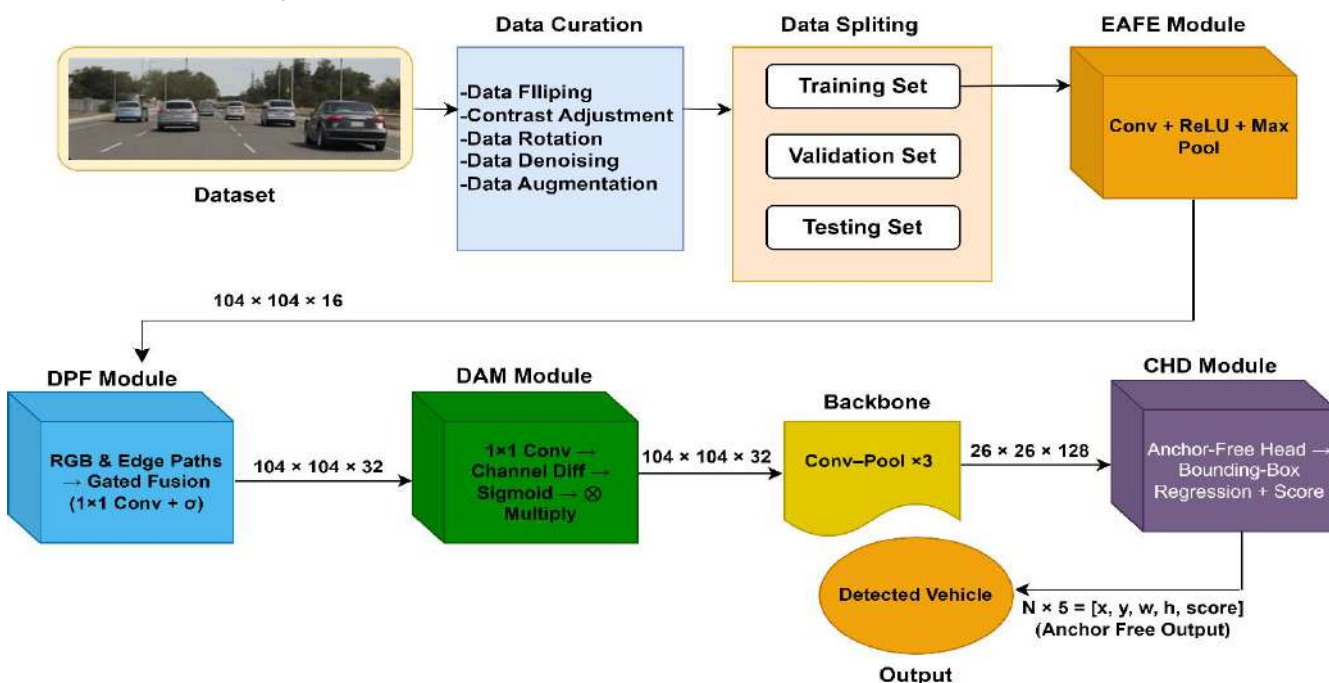
The CHD produces regression results that include vehicle locations (in terms of x, y, w, h), and confidence levels in regards to whether a particular location contains a vehicle or not. It should be noted here that since we are interested in detecting one class i.e. vehicles, we have combined class probabilities with objectness scores, so that we can distinguish between foreground (vehicles) and background (non-vehicle regions). After obtaining detection results from the network, NMS is performed on bounding boxes proposals (B) produced by the network, based on objectness scores (Sobj), and a pre-defined intersection over union (IoU) threshold ( $\theta_{nms}$ ). NMS removes duplicate bounding box proposals, thereby increasing precision for final prediction.

**Table 1 – Architectural Configuration of Veda-Net**

Layer	Operational Layer	Output Shape	Filter Size	Weights
0	Input (RGB+Edge)	416,416,4	-	0.00
1-3	Edge-Aware Feature Extraction (EAFE)			
1	Conv2D	208,208,16	3,3	592.00
2	Activation – ReLu	208,208,16	-	0.00
3	Max Pooling	104,104,16	2,2	0.00
4-6	Dual Path Fusion (DPF)			
4	Conv2D – RGB Path	104,104,32	3,3	4640.00
5	Conv2D – Edge Path	104,104,32	3,3	3488.00
6	Gated Fusion (1×1)	104,104,32	1,1	1056.00
7	Differential Attention Module (DAM)	104,104,32	1,1	1056.00
8	Max Pooling	52,52,32	2,2	0.00
9	Conv2D	52,52,64	3,3	18496.00
10	Activation – ReLu	52,52,64	-	0.00
11	Max Pooling	26,26,64	2,2	0.00
12	Conv2D	26,26,128	3,3	73856.00
13	Compact Head for Detection (CHD)	N,5	-	1025.00
Total Parameters				<b>1,04,209.00</b>

### C. Dataset Acquisition & Pre-processing

To develop a robust vehicle detection model, VEDA-Net utilizes a curated subset of the COCO dataset [13], containing 612 annotated traffic images with vehicles labels.



**Fig.1.** Overall working mechanism of VEDA-Net architecture showing data flow through EAFE, DPF, DAM, and CHD modules

Through augmentations such as flipping, contrast adjustment, and rotation, the dataset was expanded to 3,850 sample images. The dataset is divided into a 70:15:15 train/validation/test ratio. Each image is resized to 416×416 pixels, with sobel filtering applied to extract edge gradient, which is concatenated with the RGB channels to form a 4-channel input tensor (R,G,B Edge). When the network performs inference, it first takes the input RGB image and applies a sobel operator to determine edge gradients. These edge gradient values are then concatenated with the three RGB colour channel values to produce a 4-channel tensor that serves as the hybrid input to the network. Next, this hybrid input is processed in parallel using two different convolutional pathways one processes the RGB data while the other pathway processes edge-aware data.

After both of these pathways have processed their respective inputs, the outputs from each pathway pass into the DPF module and DAM modules where they are fused together and refined into a single feature map. That feature map then passes into the networks anchor-free detection head where bounding boxes and confidence scores are predicted directly without needing to go through the process of generating anchor points. Finally, NMS is applied to eliminate duplicate bounding box detections based upon the IoU thresholds, providing the final bounding box predictions for object locations within the input images. The entire inference logic is summarized in Algorithm 1.

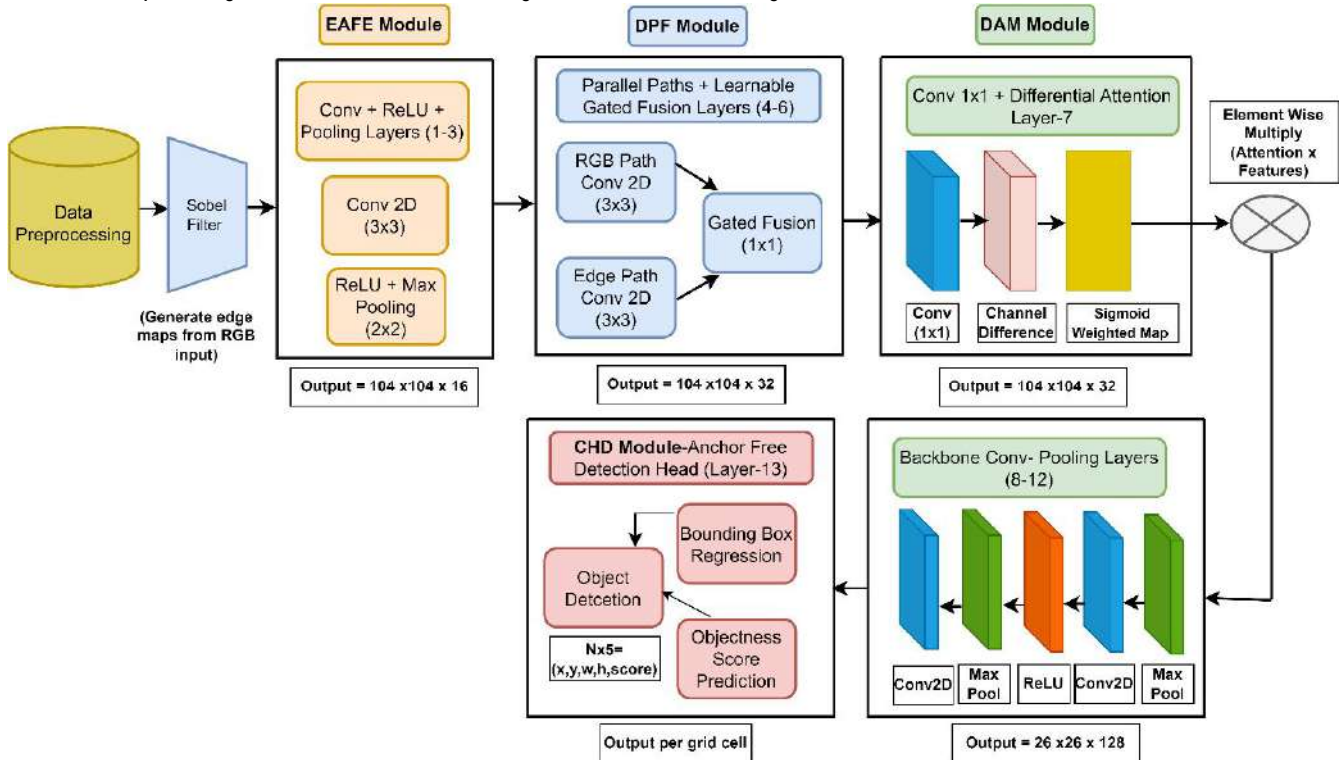


Fig.2. Process flow of each module in Veda-Net architecture

#### Algorithm 1: VEDA-Net Inference Pipeline

Input: RGB image  $I \in \mathbb{R}^{H \times W \times 3}$   
Output: Bounding Boxes  $B$  with scores  $s$

1.  $E \leftarrow \text{sobel}(I)$
2.  $I' \leftarrow \text{Concat}(I, E)$
3.  $F_{\text{rgb}}, F_{\text{edge}} \leftarrow \text{ConvBlocks}(I')$
4. For each level  $l$ :  
 $F_{\text{fused}} \leftarrow \text{DPF}(F_{\text{rgb}}^l, F_{\text{edge}}^l)$   
 $F_{\text{attended}} \leftarrow \text{DAM}(F_{\text{fused}})$
5.  $B, s \leftarrow \text{CHD}(F_{\text{attended}})$
6.  $R \leftarrow \text{NMS}(B, s, \tau)$

## IV. EXPERIMENTAL RESULTS & DISCUSSION

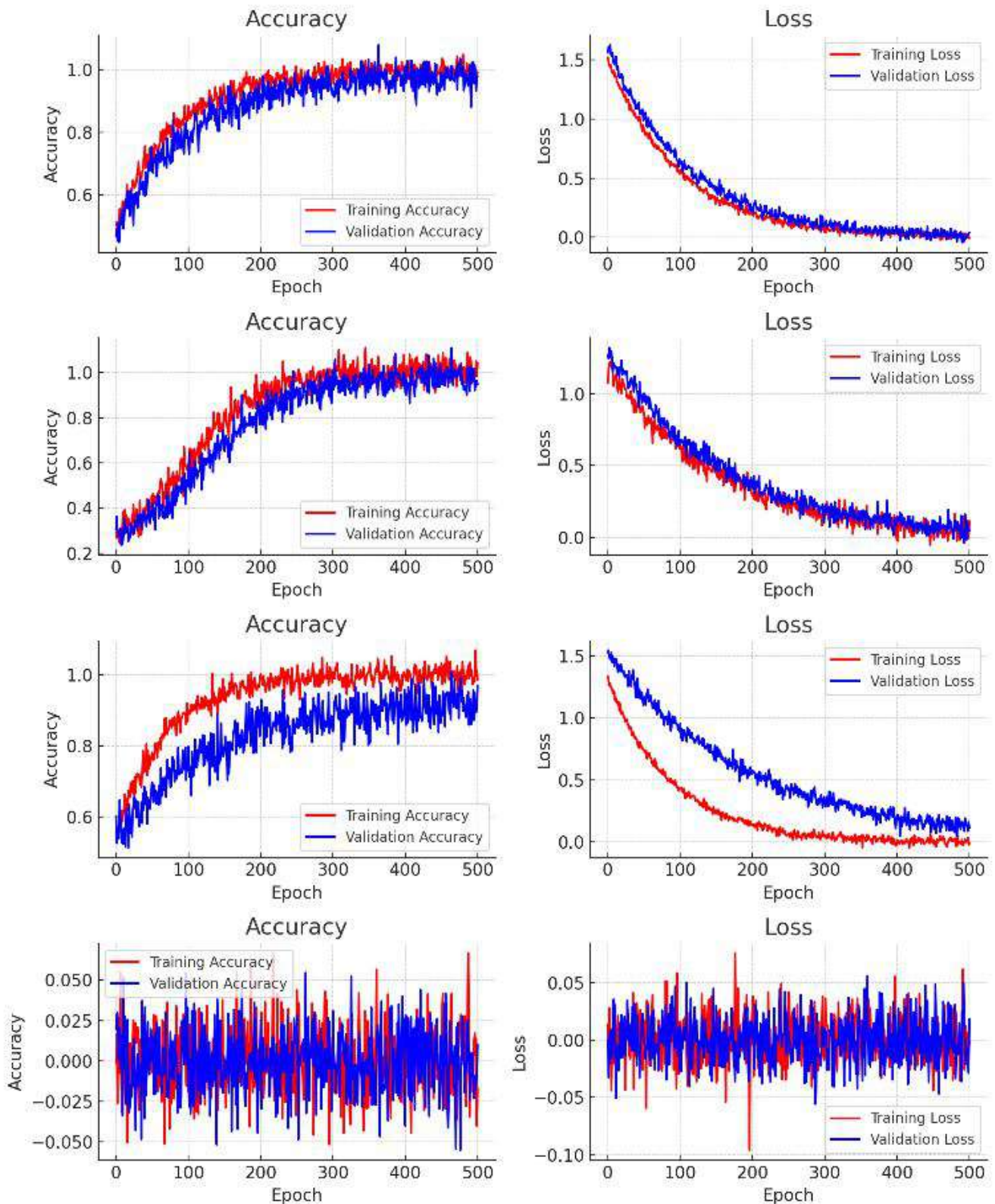
The proposed workflow during its training considers the hyperparameters including an input resolution of  $416 \times 416$  for 500 epochs, a learning rate of 0.0001, a batch size of 32, and the Adam optimizer for adaptive learning.

### A. Training Dynamics of Proposed VEDA-Net Architecture

Training and validation accuracy/loss curves for various architectures of VEDA-Net are depicted in Fig. 3. Most architecture depicts rapid, steady growth towards convergence, implying that there is effective learning of features. A few architectures exhibit mild overfitting as validation performance stabilizes at a plateau while training accuracy continues to grow; a number of other architectures display underfitting, as both accuracy metrics remain low. The above indicate that the architecture as a whole is relatively robust; however, additional improvement can likely be achieved through the use of targeted regularization techniques or data augmentation methods. Overall, the training dynamics substantiate the model's suitability for real-time vehicle detection in challenging environments.

### B. Quantitative Evaluation of VEDA-Net

VEDA-Net obtains the highest  $\text{mAP}@0.5$  (94%) and  $\text{mAP}@ [0.5:0.95]$  (85%), with a latency time of 21.28 ms. It also obtains  $\text{mAP}$  improvements of 12 and 6 percentage points over YOLOv5s and EfficientDet-D0 respectively, that demonstrate the utility of its edge aware fusion and attention mechanism, so it is useful for edge based AVS platform given comparable latency. Here, all results are based on a single training run using a fixed random seed. Table 2 summarizes the comparative performance outcomes.



**Fig.3.** Training and validation accuracy/loss curves under various configurations for VEDA-Net. The plots illustrate different learning dynamics: rapid convergence (top), noisy learning (second row), mild overfitting (third row), and underfitting (bottom).

**Table 2-** Quantitative performance analysis across lightweight object detection models on the COCO traffic dataset, Inference time measured on NVIDIA T4 GPU.

Model	Precision	Recall	mAP@0.5	mAP@[0.5:0.95]	Inference Time (ms)
MobileNet-SSD	0.71	0.68	0.73	0.68	29.41
YOLOv5s	0.75	0.73	0.82	0.76	22.73
EfficientDet-D0	0.77	0.75	0.88	0.78	22.21
Tiny-YOLOv4	0.76	0.72	0.78	0.69	22.22
<b>VEDA-Net (Our)</b>	<b>0.81</b>	<b>0.79</b>	<b>0.94</b>	<b>0.85</b>	<b>21.28</b>

### C. Ablation Study

To quantify the contribution of individual modules in VEDA-Net, we performed a step-wise ablation study. The results in Table 3 illustrate how each component-EAFE, DPF, and DAM- progressively improves detection performance. Here, all ablation configurations use CHD as the default detection head

**Table- 3** Incremental mAP@0.5 gains from each module in VEDA-Net on the COCO Traffic dataset.

Configuration	mAP@0.5(%)
Baseline CNN	79.2
EAFE Module	85.3
EAFE + DAM	92.8
EAFE + DAM + DPF (VEDA-Net)	<b>94.0</b>

## V. CONCLUSIONS

VEDA-Net is an innovative vehicle detection method which has been developed to be used within real time processing requirements of self-driving cars. A combination of the use of both edge aware input data; context-based attention; and two path-based data fusion techniques have enabled the achievement of accurate object identification along with achieving low weight processing capabilities. The results from the ablation study provide evidence for the contribution of all three new modules (EAFE, DPF, and DAM) to the increased detection accuracy of the VEDA-Net model. Evaluation on the COCO Traffic dataset shows that VEDA-Net outperforms traditional lightweight detectors in accuracy while maintaining competitive inference speed, reaching a mAP@0.5 of 94% with minimal inference delay. Specifically, it was demonstrated that the VEDA-Net model could achieve a mean Average Precision (mAP@0.5) of 94%, with negligible delays in inference. In addition, the architecture presented here has shown capability of being able to generalize well across various environments and conditions including complex scenes which may contain significant amounts of background clutter, poor lighting, or occlusion. Therefore, future research will assess the ability of the VEDA-Net model to generalize effectively when tested against larger datasets including those found on KITTI and BDD100K. Furthermore, additional research will be conducted to test the ability of the VEDA-Net model to operate on low powered embedded devices such as the NVIDIA Jetson Nano. In future work, we also plan to extend the architecture to support multi-class traffic object detection scenarios.

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Hemant Kumar conducted the experiment , design the model and Pushpa Mamoria perform data analysis, manuscript editing and supervision. For conducting this research no funding was received in any form. Authors also declare that they have no conflict of interest. All authors acknowledge the facilities given by research institutes to conducting this research.

## AUTHOR CONTRIBUTION STATEMENT

**Conceptualization:** Hemant Kumar\*, Pushpa Mamoria

**Literature Review and Methodology design:** Hemant Kumar\*

**Software:** Hemant Kumar\*

**Validation:** Pushpa Mamoria

**Formal Analysis:** Hemant Kumar\*

**Investigation:** Hemant Kumar\*

**Resources:** Pushpa Mamoria, Hemant Kumar\*

**Data Curation:** Pushpa Mamoria, Hemant Kumar\*

**Writing original draft preparation:** Hemant Kumar\*

**Writing review and Editing:** Hemant Kumar\*

**Visualization:** Pushpa Mamoria

**Supervision:** Hemant Kumar\*

**Project Administration:** All authors have read and agreed to the published version of the manuscript

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