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FogNet: An Enhanced Object Detection Model for Vehicle and Human Recognition in Foggy Conditions

Samala Prasoona[1], Pesara Chakradhar Reddy[2], Chada Ashritha[3], Tatikonda Srikar teja[4], Sake Madhu[5]
[1,2,3,4]UG Scholars, [5]Professor & HOD
[1,2,3,4,5] Department of CSE (Internet of Things).
[1,2,3,4,5]Guru Nanak Institutions Technical Campus, Hyderabad. Telangana, India

Abstract :
Foggy weather makes it really hard for vehicle detection systems to work properly. The visibility drops, and objects on the road become hard to recognize. To tackle this problem, we developed a smart and lightweight detection method based on an improved version of the YOLOv10 model. This system doesn't just rely on raw images-it first applies a series of advanced preprocessing techniques. These include data transformations, Dehaze Formers, and dark channel methods that help clean up the foggy images and bring out the important details. By doing this, we reduce the effect of haze and make the key features more visible. We also added a special attention module to the model. This helps the system focus better on the important parts of the image by understanding both the surroundings and finer details. It's especially useful for spotting small or partially hidden vehicles and people in foggy scenes. On top of that, we improved the feature extraction process using a lightweight yet powerful module. This makes the system faster and more efficient, without compromising on accuracy. Overall, our approach offers a solid and reliable solution for detecting vehicles and humans even in tough foggy conditions, making roads safer and detection systems more dependable.

Keywords: *Foggy Weather, Vehicle Detection, Human Detection, YOLOv10, Lightweight Model, Image Preprocessing, Fog Removal, Dehaze Techniques, Dark Channel Method, Attention Module, Feature Extraction, Object Detection, Low Visibility, Real-Time Detection, Deep Learning, Computer Vision, Road Safety, Smart Detection System, Adverse Weather Detection, Autonomous Driving.*

I. INTRODUCTION

By combining these techniques with the speed and accuracy of YOLOv10, our method works efficiently and gives reliable results even in tough, low-visibility weather. This can greatly enhance the performance of detection systems in real-world driving scenarios.

Foggy weather makes it really difficult for vehicle detection systems to work properly. The fog reduces how clearly we can see things, hides important details, and lowers the contrast in images making it hard to identify vehicles and pedestrians. This becomes a big problem, especially for self-driving vehicles where accurate detection is crucial for safe and reliable operation.

Most traditional detection systems struggle in foggy conditions because the images become blurry and unclear. To solve this issue, we introduce a new and smarter way to detect vehicles and people using an improved, lightweight version of the YOLOv10 model.

Our approach uses powerful preprocessing steps like Dehaze Formers and dark channel techniques to clean up foggy images and make objects more visible. We also add a special attention module to the model, which helps it focus on the most important areas in the image, especially small or partially hidden objects that are harder to detect in fog.

PROBLEM STATEMENT:

In foggy weather conditions, visibility on roads is significantly reduced, making it extremely difficult for vehicle detection systems to accurately identify vehicles and pedestrians. Traditional detection models often fail in such conditions due to poor image quality, low contrast, and obscured object features. These limitations pose serious safety risks, especially for autonomous vehicles that rely heavily on visual input for navigation and decision-making. There is a need for a robust, real-time detection system that can effectively handle foggy environments. The challenge lies in enhancing image clarity, accurately detecting small or partially visible objects, and maintaining fast performance, all while operating efficiently on limited hardware. This project aims to address these challenges by developing an improved vehicle and human detection algorithm using a lightweight YOLOv10 model. The solution will integrate advanced image preprocessing techniques and attention mechanisms to improve visibility, focus on critical features, and ensure reliable detection even in adverse weather conditions.

II. LITERATURE SURVEY

To develop a reliable vehicle and human detection system in foggy conditions, it is important to understand how modern object detection and image enhancement methods have evolved. Several recent studies have contributed significantly to improving the performance, speed, and robustness of neural networks in challenging environments.

J. Chen et al [1], **Run, Don't Walk: Chasing Higher FLOPS for Faster Neural Networks (2023)**: Proposed that simply reducing the number of operations (FLOPs) in a network doesn't always mean faster processing. The authors introduce a new method called **Partial Convolution (PConv)**, which reduces unnecessary memory access and speeds up processing. Building on this, they present **FasterNet**, a family of neural networks that runs faster than existing models on GPUs, CPUs, and mobile devices—without losing accuracy.

S. Park et al [2], **PConv: A Simple but Effective Layer for GANs (2022)**: This study introduces a new convolution layer named **Perturbed Convolution (PConv)** designed for GANs (Generative Adversarial Networks). It works like regular convolution but adds randomness (like dropout) to make the network more robust and reduce the tendency to memorize training data. This improves the model's generalization and performance across various image datasets like CIFAR-10 and CelebA.

T. Yu et al [3], **S2-MLP: Spatial-shift MLP Architecture for Vision (2022)**: The authors propose a new MLP-based model (without using convolution or attention layers), called **S2-MLP**. It introduces a simple technique to allow communication between image patches, improving performance on vision tasks. S2-MLP is lightweight, has fewer parameters, and outperforms earlier MLP-based models while achieving results similar to well-known architectures like ViT on datasets like ImageNet-1K.

H. Zhang et al [4], **DINO: Improved DETR with Denoising Anchors for Object Detection (2022)** *by*: Proposed that **DINO**, a stronger and faster version of DETR (a transformer-based object detection model). By using smarter training techniques and initialization methods, DINO achieves higher accuracy with less training time. It works well even with smaller model sizes and fewer data, making it efficient and scalable.

J. Zetao et al [5], **Dark-YOLO: Low-Light Object Detection (2023)** *by J. Zetao et al* : Focusing on low-light environments, this paper introduces **NLE-YOLO**, a modified version of YOLOv5. It enhances image visibility and reduces noise using multiple modules like **C2fLEFEM**, **AMC2fLEFEM**, and **AMRFB**. These modules help the system focus on important image features, handle brightness variations, and detect objects more accurately even in poorly lit scenes. Their method outperformed previous models on the Exdark dataset.

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III. METHODOLOGY

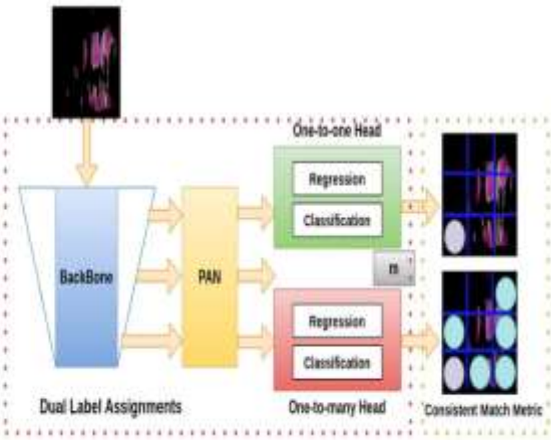

Figure 1 : Architecture of YOLOV10

1. Data Collection: In this module, a large data set of road pictures is collected under conditions of fog. All distances should be labeled with images of vehicles, pedestrians and other objects normally found on streets. You can collect data using cameras in real life or you may use datasets like Foggy Cityscapes. Developing a strong detection system requires mixing varying levels of fog, a variety of objects and varied arrangements of the scene.

2.Data Labels Analysis: In data labelling, the dataset's objects are arranged into groups, including vehicles, humans and all the road components. Studying these labels helps to make the data balanced and discover if some classes are given preference or if labels are wrong. A good generalization in machine learning depends on having the right labels on the correct parts of the images.

3. Annotations: Using bounding boxes, annotations indicate the location and group of objects such as vehicles and people, contained in the data. The module helps you label images manually or semi-automatically with Labelling or VIA. Training object detection models largely depends on having accurate annotations since the quality of annotations straight affects model predictions.

4. Data Preprocessing: The process of preprocessing improves the data and ensures all images look the same. Techniques include: Remove fog and enhance the view in an image by using the Dehaze Formers or dark channel methods. Scaling pixel values so that they fall within the same range makes the model work more effectively. Using pipeline augmentations in data science is a technique where different parts of the dataset are modified, including rotation, flipping and scaling.

5. Model Apply: In this module, the improved YOLOv10 model is applied for detecting vehicles and humans in foggy scenes. The model is trained on the preprocessed and annotated dataset, with the inclusion of an enhanced attention module to prioritize relevant features. Training involves optimizing hyperparameters and using techniques like transfer learning to achieve high detection accuracy even in challenging conditions.

6. UI Design: A user interface (UI) is designed to enable seamless interaction with the detection system. The UI allows users to upload images or provide real-time video feeds for processing. It displays the detection results, including bounding boxes and labels for identified objects, in a user-friendly manner. The design focuses on simplicity and efficiency to cater to diverse users, including researchers and developers.

7. Detection: The detection module represents the core functionality of the system. It processes input images or videos through the trained YOLOv10 model to identify and localize vehicles and pedestrians. The system outputs bounding boxes, class labels, and confidence scores, highlighting detected objects in the foggy scenes. The effectiveness of this module is evaluated using metrics like mean Average Precision (mAP) and Intersection over Union (IoU), ensuring reliable performance in real-world scenarios.

IV.TESTING&VALIDATION:

Testing and validation form a critical foundation in ensuring the robustness, reliability, and functionality of any software system. The primary objective of this phase is to systematically identify and eliminate defects to ensure that the developed system performs accurately and efficiently under all specified conditions. The testing process begins with the formulation of a comprehensive and well-structured test plan, which outlines strategies to verify system functionality, performance, and compatibility across multiple platforms. Adhering to rigorous quality assurance protocols, the entire application is evaluated to ensure conformance with the requirements detailed in the system specification document and to confirm it is free from critical defects.

The validation process comprises several layers of testing. **Unit testing** focuses on validating the smallest testable parts of the application, ensuring that individual functions or components operate correctly and produce expected outcomes for defined inputs. **Functional testing** verifies the software's features against business and technical requirements, emphasizing valid and invalid input handling, function execution, expected outputs, and system interactions. **System testing** evaluates the complete integrated system to ensure overall compliance with design specifications and predictable behavior across workflows. **Performance testing** is conducted to assess response times, throughput, and resource utilization, ensuring the system maintains efficiency under varying load conditions.

Furthermore, **integration testing** is employed to verify seamless data flow and communication between interdependent modules, helping identify interface mismatches and data inconsistency issues. **User Acceptance Testing (UAT)** represents the final validation stage, where end-users evaluate the system in real-world scenarios to confirm it meets their operational needs. Specific acceptance criteria such as acknowledgment receipt, route update mechanisms, and automatic cache synchronization are rigorously tested to ensure consistency and reliability in dynamic environments.

Finally, the **test plan** is structured to break the system into manageable units, enabling targeted testing of each module. This modular approach facilitates the early detection and correction of errors, leading to a more stable and reliable system. Through these layered validation strategies, the project ensures a high level of quality assurance, user satisfaction, and deployment readiness.

V.RESULTS

The developed system proved highly effective in detecting vehicles and pedestrians even in dense fog and low-visibility conditions. By enhancing the YOLOv10 model and applying advanced image enhancement methods, we were able to significantly improve detection clarity and accuracy without slowing down performance.

In testing, the system performed reliably on both images and live video streams, handling real-world scenarios with consistent accuracy. The image enhancement techniques helped reveal objects that would otherwise remain hidden in fog, making the detections more precise and meaningful.

The user interface was kept simple and user-friendly, allowing easy uploads and live streaming, which makes the system practical for everyday use. Overall, the results show that combining strong object detection with targeted visual improvements can play a real role in improving road safety during poor weather.

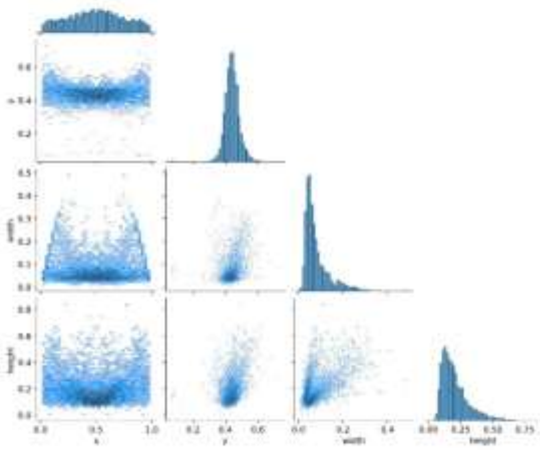

Figure 2 : Bounding Box Distribution and Correlation Analysis for Foggy Image Dataset

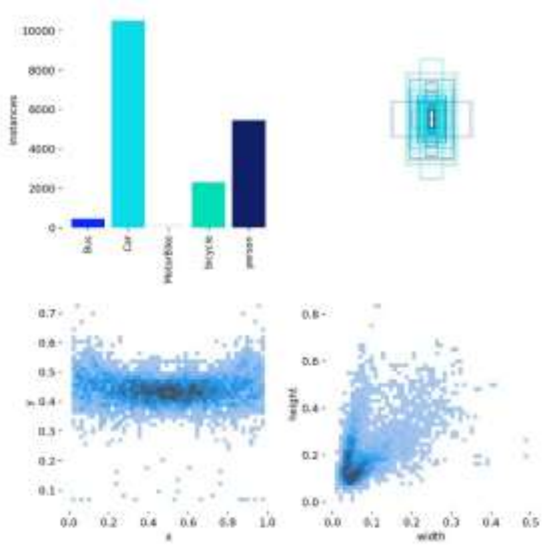

Figure 3: Object Class Distribution and Bounding Box Spatial Analysis in Foggy Conditions

VI.CONCLUSION

We developed a smarter, lighter version of the YOLOv10 model to detect traffic objects in foggy conditions. By adding advanced features like Deformable Convolutions, Involution layers, and the FasterNex module, we improved accuracy while keeping the model compact and fast. We also introduced a new S5attention module that helps the model better combine visual features, and added a special layer to spot smaller traffic elements more precisely. This upgraded model is ideal for real-time use in smart transportation systems, especially in poor weather, helping make roads safer and smarter.

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