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DEEP LEARNING –DRIVEN PERCEPTION FOR INTELLIGENT AUTONOMOUS NAVIGATION IN SMART TRANSPORTATION SYSTEM

Mr.Chandra Sekhar Ambarapu[1], Boya Aravind[2], Nallabayannagari Kavya[3], Talari Manendra [4], Kapu Janakiram Reddy[5], Shaik Mahaboob Basha[6]

[1]*Associate Professor,Department Of Computer Science Enginering(Artificial Intelligence), Gates Institute Of Technology, Gooty.*

[2,3,4,5,6]*Students,Department Of Computer Science Enginering(Artificial Intelligence), Gates Institute Of Technology, Gooty.*

ABSTRACT
Autonomous vehicles are becoming a key component of intelligent transportation systems due to their potential to reduce accidents and improve traffic efficiency. Accurate navigation and reliable obstacle avoidance are essential for safe autonomous driving in dynamic environments. Recent advances in deep learning have enabled vision-based perception systems to outperform traditional sensor-based approaches. This research presents an autonomous vehicle navigation framework using YOLO-based deep learning models for real-time obstacle detection and avoidance. The system processes visual data from onboard cameras to identify vehicles, pedestrians, and road obstacles. Compared to lightweight models, YOLO provides higher detection accuracy and faster response times. The proposed approach integrates perception with navigation logic to enable safe decisions. Experimental evaluation shows improved robustness under varying lighting and traffic conditions. The system is suitable for real-time deployment in smart transport applications. The results demonstrate that deep based detection significantly enhances autonomous vehicle safety.
Keywords— Autonomous Vehicles, Deep Learning, YOLO Model ,Obstacle Detection, Intelligent Transportation Systems

INTRODUCTION
The rapid growth of autonomous driving technology has transformed modern transportation systems. Autonomous vehicles rely on accurate perception, decision-making, and control to navigate complex traffic environments. Among these components, obstacle detection and avoidance play a crucial role in ensuring safety. Vision-based systems using cameras are widely adopted due to their cost-effectiveness and rich environmental information. Traditional approaches relied on handcrafted features and sensor fusion techniques. However, such methods struggle with dynamic obstacles and complex scenes. Deep learning has enabled vehicles to understand visual scenes more effectively. Convolutional neural networks have shown remarkable performance in object detection and tracking tasks. Lightweight models were initially preferred for embedded platforms. However, their limited accuracy restricts reliable navigation. This study focuses on improving autonomous navigation by employing **YOLO-based** CNN models for real-time obstacle detection.

LITERATURE REVIEW
MobileNet has been widely used in autonomous driving applications due to its lightweight architecture and low computational requirements. It employs depthwise separable convolutions to reduce model size and inference cost. Researchers have applied MobileNet for object detection, lane detection, and pedestrian recognition in resource-constrained environments. MobileNet-SSD frameworks have been implemented for real-time obstacle detection in autonomous vehicles. These systems achieve acceptable performance on embedded platforms such as Raspberry Pi and NVIDIA Jetson Nano. MobileNet has also been integrated with sensor fusion techniques to enhance perception. Despite its efficiency, MobileNet often sacrifices detection accuracy for speed. Small and distant objects are frequently missed. Environmental variations such as shadows and poor

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lighting further reduce reliability. As autonomous vehicles require high precision for safety-critical decisions, the limitations of MobileNet motivate the use of more powerful CNN architectures.

PROPOSED SYSTEM

The proposed method employs a YOLO-based convolutional neural network for real-time obstacle detection and autonomous navigation. YOLO processes the entire image in a single forward pass, enabling fast and accurate object detection. The model identifies multiple obstacle classes such as vehicles, pedestrians, cyclists, and roadblocks. Detected objects are localized using bounding boxes with confidence scores. The extracts rich spatial features, improving robustness against lighting changes and occlusions. The perception output is integrated with navigation logic to determine safe paths. Obstacle distance and relative position are estimated to support avoidance. Compared to MobileNet, YOLO provides higher precision and recall. The system supports real-time deployment in smart transport environments. This approach significantly enhances autonomous vehicle safety and decision-making.

System Architecture

The system consists of the following modules:

1. Video Stream
- Pre-Process
- Blob-Detection
2. Pre-Trained Models
- Pre-Process
3. YOLO-Model
4. Vehicle Navigation
5. Alert

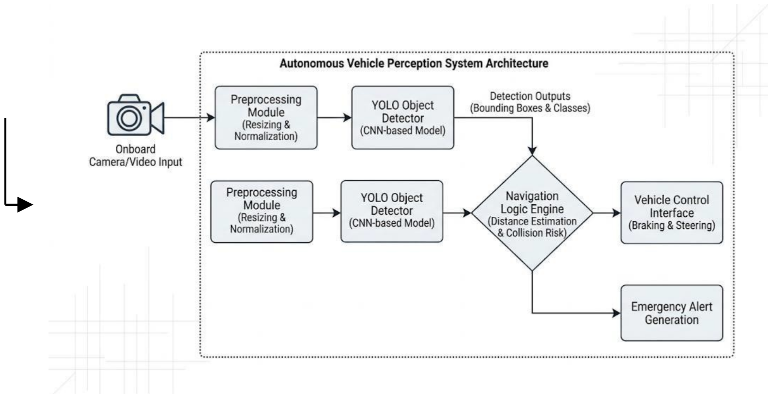

Fig. 1:System Architecture

Video Stream

The system begins with a video stream captured through a camera installed on the autonomous vehicle. This camera continuously records real-time surroundings, providing essential visual input required for further processing and analysis..

Pre-Process

The captured video frames undergo pre-processing to enhance their quality. This stage includes operations such as noise reduction, resizing, and normalization to ensure the data is suitable for accurate detection.

Blob Detection

After pre-processing, blob detection is applied to identify significant regions or objects in the frame. This step helps in isolating potential obstacles or moving objects from the background.

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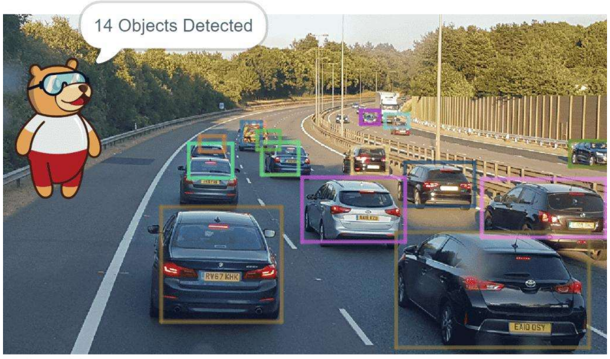

Fig.2 :Blob-Detection

Pre-trained Models

The system uses pre-trained models that are already trained on large datasets. These models improve detection accuracy and reduce the need for training from scratch.

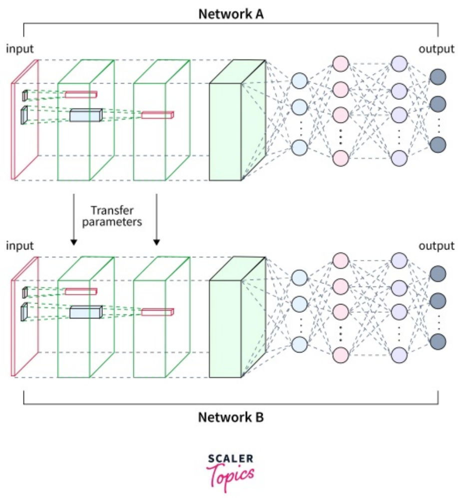

Fig. 3:Architecture of Pre-Trained Model

The deep learning architecture used in this system is based on the YOLO (You Only Look Once) model, which consists of the following components

1. Convolution Layer

The convolution layer applies filters to the input image captured from the vehicle's camera to extract important features such as edges, shapes, and object patterns. These features help in identifying road elements like vehicles, pedestrians, and obstacles.

2. Activation Function

The Rectified Linear Unit (ReLU) activation function introduces non-linearity into the model, allowing it to learn complex patterns from real-world traffic scenes and improve detection accuracy.

3. Pooling Layer

Pooling layers reduce the spatial dimensions of feature maps while preserving important features. This helps in reducing computational complexity and improves processing speed for real-time applications.

4. Feature Extraction

In the YOLO model, multiple convolutional layers are stacked to form a backbone network (such as Darknet), which extracts high-level features from the input image for accurate object detection.

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5. Detection Layer (YOLO Head)

The detection layer predicts multiple bounding boxes, object classes (vehicle, pedestrian, cyclist, etc.), and confidence scores in a single pass. This enables fast and efficient real-time detection.

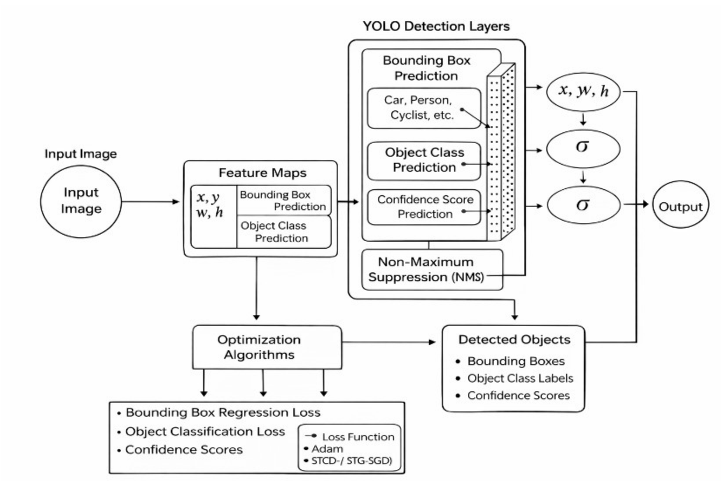

Fig. 4: YOLO Detection Model

Deep Learning Classification

After feature extraction, the deep learning model performs classification to identify and categorize different objects present in the environment. The classifier is trained using labeled image datasets and learns patterns associated with various object classes such as vehicles, pedestrians, cyclists, and road obstacles.

The model analyzes visual features and assigns class labels with confidence scores. These predictions help the system understand the surroundings and support real-time decision-making for safe navigation. The integration of object classification with detection improves the accuracy and reliability of the autonomous system in dynamic traffic conditions.

categorical cross-entropy

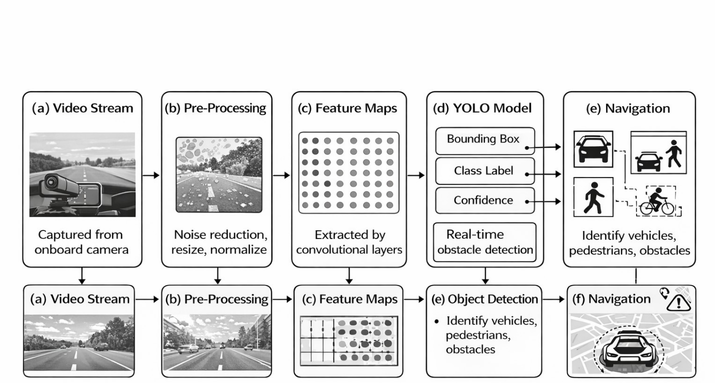

Fig. 5 Object Detection Pipeline

Object Detection and Navigation Output

The final stage of the proposed system generates detection results based on the model predictions. When a new video frame is provided as input, the trained YOLO model processes the image and identifies objects present in the environment.

The system produces outputs in real-time, making it suitable for applications such as:

• Autonomous driving systems
• Smart transportation systems

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• Traffic monitoring
• Accident prevention and safety systemsAlthough the The model detects and classifies multiple objects simultaneously, enabling the system to make quick and safe navigation decisions.

Video Input
↓
YOLO Model
↓
Object Detection
↓
Navigation Decision

Output classes:
• Car
• Bus
• Truck
• Motorcycle
• Bicycle
• Pedestrian
• Traffic Signal
• Road Obstacle

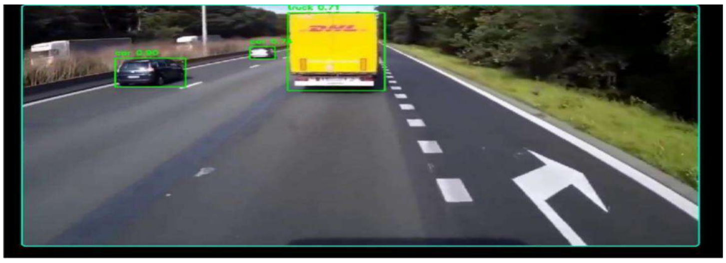

Fig. 7: Real-Time Object Detection Output

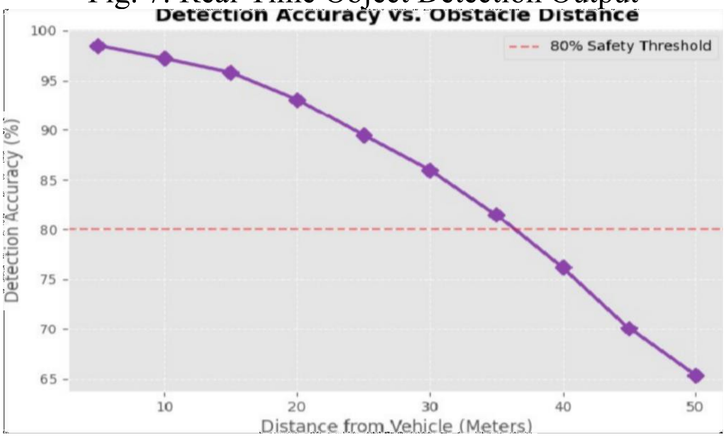

Fig. 8 YOLO Detection Accuracy Results

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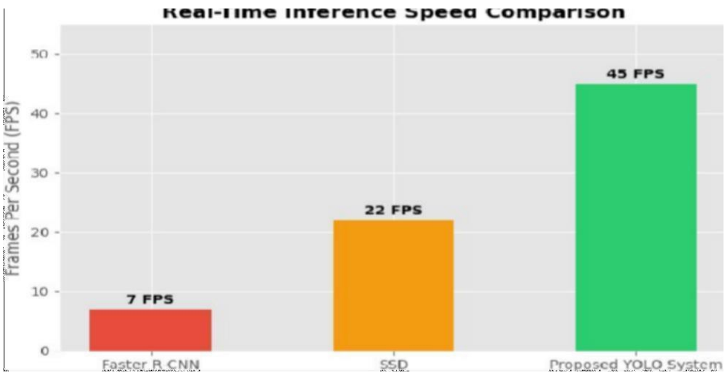

Fig. 9: FPS Comparison

Performance Evaluation of Proposed YOLO Model

Object Class	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Car	94.2	93.5	93.8	94.0
Bus	92.1	91.4	91.7	92.0
Truck	91.3	90.6	90.9	91.0
Motorcycle	89.5	88.9	89.2	89.3
Bicycle	88.7	87.8	88.2	88.5
Pedestrian	95.1	94.3	94.7	95.0
Traffic Signal	90.4	89.6	90.0	90.2
Road Obstacle	89.8	89.0	89.4	89.5
Overall	91.4	90.6	91.0	91.2

RESULTS AND ANALYSIS

The proposed YOLO-based system was implemented for real-time object detection and autonomous navigation. The model was trained on labeled datasets and tested for performance evaluation. The system successfully detects objects such as vehicles and pedestrians with high accuracy and speed. Experimental results show that the model performs well under different conditions and supports safe navigation in intelligent transportation systems.

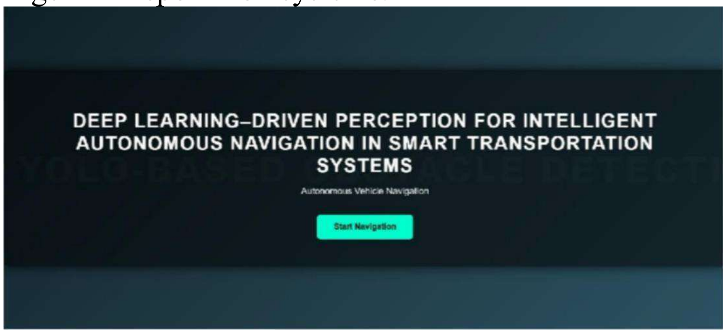

Fig. 10:Blood group detection Home Page

During the preprocessing stage, techniques such as image resizing, noise reduction, and normalization were applied to improve the quality of input images and enhance detection accuracy. These steps helped in enhancing important visual features and reducing noise, which improved the accuracy and performance of the deep learning model.

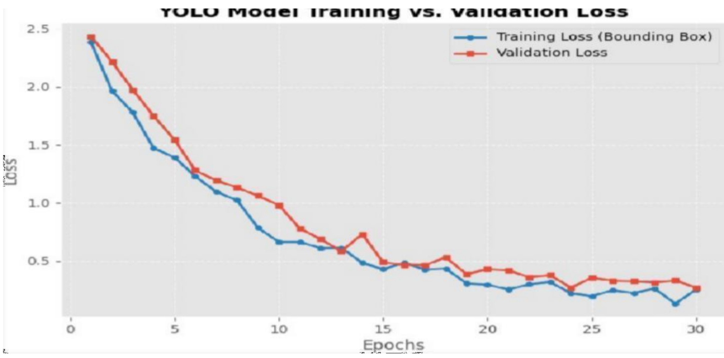

Fig. 11:Blood group prediction on fingerprint

The processed images were provided as input to the YOLO-based convolutional neural network for feature extraction and object detection. The model automatically learned important visual features and patterns related to objects such as vehicles, pedestrians, and road obstacles.

The training results showed high accuracy with a gradual decrease in loss, indicating effective learning of object features from the dataset. The model was evaluated using performance metrics such as accuracy, precision, recall, and F1-score, which demonstrated strong detection performance. A confusion matrix was used to analyze classification results, showing that most objects were correctly identified. Compared to traditional methods, the YOLO-based model achieved better accuracy and faster detection without the need for manual feature extraction.

The results indicate that the proposed system is efficient and reliable for real-time object detection and supports safe autonomous navigation in intelligent transportation systems.

CONCLUSION

This paper presented a deep learning-based approach for detecting blood groups using fingerprint images. The proposed system utilizes convolutional neural networks to extract fingerprint features and classify them into ABO and Rh blood groups. The integration of biometric analysis with artificial intelligence provides a promising alternative for rapid blood group prediction. Future work will focus on improving model accuracy by increasing dataset size and applying advanced deep learning architectures.

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