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YOLOv10-Driven Enhanced Vehicle Detection in Low-Light On-Board Environments

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Abstract: Accurate vehicle detection in low-light environments is crucial for improving safety in intelligent transportation systems by identifying vehicles under challenging conditions such as poor illumination, motion blur, glare, and visual noise. To reduce performance degradation and computational limitations, a YOLOv10-based lightweight detection framework is proposed that effectively captures both fine object features and global scene information. The system relies solely on enhanced image inputs, ensuring hardware simplicity and easy deployment without requiring additional sensors or inputs. It uses an optimized architecture with pre-processing techniques and advanced training strategies to improve detection accuracy and efficiency. As a result, the model achieves strong generalization and reliable performance in real-time low-light driving scenarios.
Keywords:YOLOv10, Vehicle Detection, Low-Light Environments, Object Detection, Autonomous Driving

I. INTRODUCTION

Accurate vehicle detection is widely used for ensuring safety and efficiency in intelligent transportation systems and autonomous driving, with vision-based systems being the most common due to their flexibility and real-time capabilities. However, low-light conditions such as poor illumination, motion blur, glare, and noise pose serious challenges to detection performance. To address this, advanced object detection methods like YOLOv10 play a vital role in improving detection accuracy under challenging environments. This enhances the reliability of systems in applications such as traffic monitoring, collision avoidance, and autonomous navigation. Over time, various detection methods have been developed, including traditional approaches and deep learning-based models.These limitations highlight the need for more efficient and lightweight vehicle detection solutions.

II. LITERATURE SURVEY

K.Zhu, H.Lyu, and Y.Qin (2025) This paper presents an improved YOLOv5 model for detecting small, distant, and occluded road vehicles in complex environments, enhancing accuracy and robustness. It introduces architectural modifications and feature fusion strategies, enabling better detection performance, which is important for autonomous driving and intelligent traffic monitoring systems.

J.Guo, M.Shao, X.Chen, Y.Yang, and E.Sun (2025) This paper introduces KSC-YOLOv5, an improved model designed for nighttime vehicle detection, enhancing performance under low-light conditions. Using improved feature extraction techniques, it effectively handles challenges such as noise and poor visibility, improving detection accuracy in traffic surveillance systems.

III. EXISTING SYSTEM

The existing system uses a YOLOv8-based approach for vehicle detection, leveraging an advanced architecture to achieve high accuracy and fast inference in well-lit environments. This method enhances detection performance through anchor-free prediction and improved feature extraction without requiring additional processing modules, maintaining efficiency while ensuring reliable detection capability.

Existing System Disadvantages

- Prone to performance degradation in low-light conditions
- Limited fine-grained feature extraction in challenging environments

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- High computational cost for larger model variants
- Lower adaptability to noise, glare, and occlusions

Proposed System

This project uses YOLOv10, an advanced real-time object detection model, for efficient vehicle detection in low-light environments. It extracts both fine object details and global contextual features to accurately detect vehicles under challenging conditions. The model's optimized architecture, along with pre-processing techniques, ensures high accuracy while maintaining fast performance. This balance makes it suitable for reliable and real-time intelligent transportation applications.

Proposed System Advantages:

- High Accuracy in Low-Light Detection
- Better Generalization Across Environments
- Real-Time Processing Capability
- Scalable and Practical for development

IV. SYSTEM ARCHITECTURE

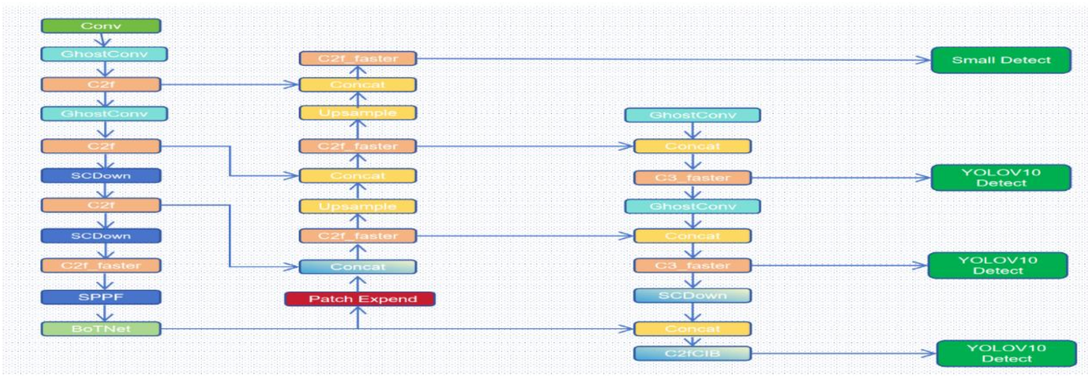

Figure 1: System Architecture

This diagram shows an object detection architecture using optimized layers like GhostConv, C2f, and C3 to extract and fuse multi-scale features. It uses advanced modules and multiple detection heads to achieve accurate and fast detection of objects at different sizes.

Methodology

1. Data Collection and Preprocessing Module:

This module collects and preprocesses fingerprint images (real and spoof) using techniques like resizing, normalization, and noise removal.It applies data augmentation and splits the dataset into training, validation, and testing sets for effective YOLOv8n model training.

2. Feature Extraction:

In this module, YOLOv8n extracts both local and global fingerprint features.Its efficient architecture enables accurate, real-time liveness detection with low computational complexity.

3. Model Training and Optimization:

This module trains the YOLOv8n model to classify fingerprints as live or spoof using supervised learning. Optimization and regularization techniques ensure fast convergence, high accuracy, and strong generalization against unseen attacks.

4. Liveness Detection and Classification:

This module uses the trained YOLOv8n model for real-time classification of fingerprints as live or spoof. It analyzes fine patterns and outputs an authenticity score, ensuring fast and accurate biometric authentication.

5. Performance Evaluation:

This module evaluates the YOLOv8n model using metrics like Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. It also tests robustness and compares with other methods, showing high accuracy and fast performance for real-world use.

6. Deployment and User Interface:

This module deploys the trained YOLOv8n model into a user-friendly application for real-time fingerprint authentication.It ensures fast, portable, and efficient performance with an easy GUI for practical use in security systems.

V. IMPLEMENTATION

The implementation phase converts the conceptual design of the Fingerprint Liveness Detection system into a real-time working application. This stage involves setting up the development environment, preprocessing fingerprint datasets, training the deep learning model, and integrating the system for real-time detection.

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The system is designed to accurately distinguish between live and spoof fingerprints using advanced deep learning techniques.

Algorithm Used

Existing Algorithm

CNN

Existing FLD methods use CNNs to detect spoof fingerprints by extracting local features, but they struggle with global patterns and generalization to unseen attacks.They also require high computational resources and complex architectures, leading to overfitting and highlighting the need for lightweight and efficient solutions.

Proposed Algorithm

YOLOv8n:

YOLOv8n is a lightweight object detection model designed for real-time performance and high accuracy, predicting object locations and classes from image grids. It uses an optimized backbone and multi-scale feature learning to capture both fine and global details, making it suitable for resource-constrained environments like mobile and embedded systems.

VI. EXPERIMENTAL RESULTS

REGISTRATION PAGE :

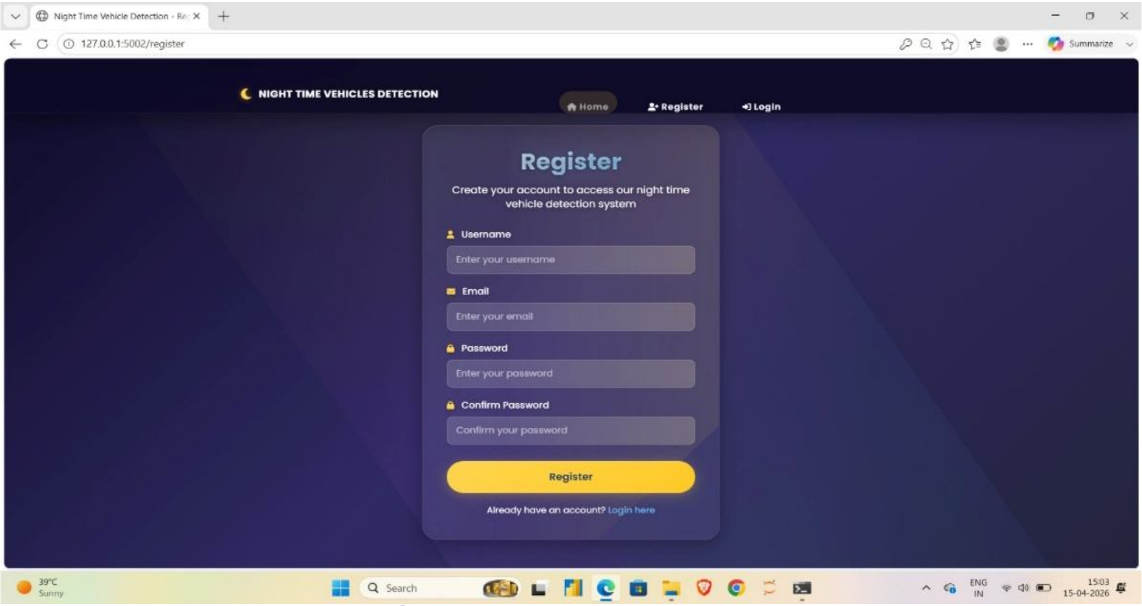

Figure 1: REGISTRATION PAGE

This page provides a registration interface with fields for email, password, and confirmation, along with a register button and a login link for existing users.

DETECTION PAGE :

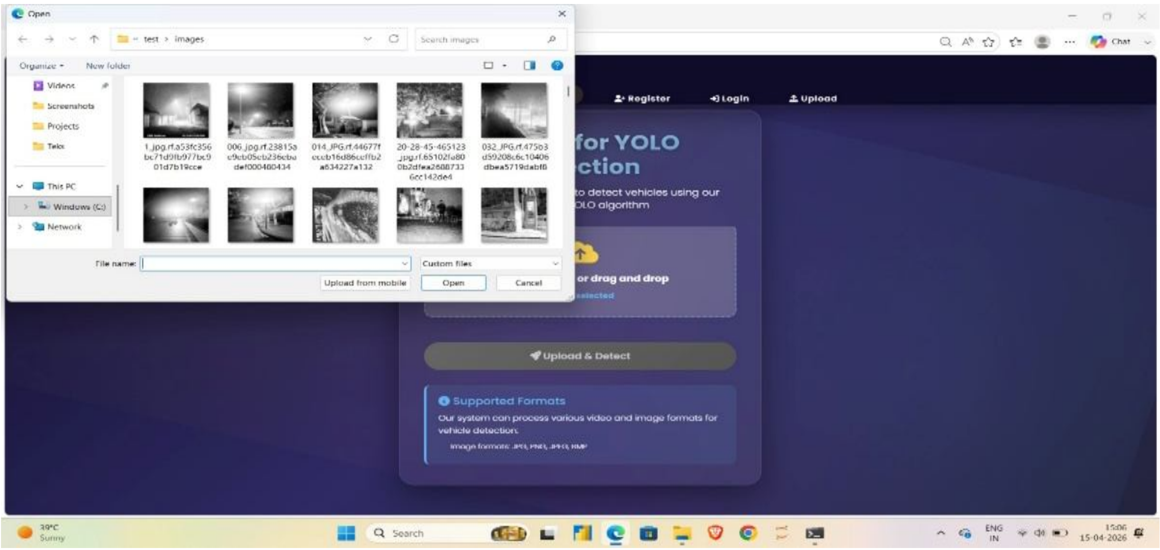

Figure 2: DETECTION PAGE

This page represents a fingerprint liveness detection system where users can upload or capture fingerprint images to verify if they are real or fake. It includes options for detection, analytics, and performance, ensuring secure and reliable fingerprint authentication.

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VERIFICATION PAGE:

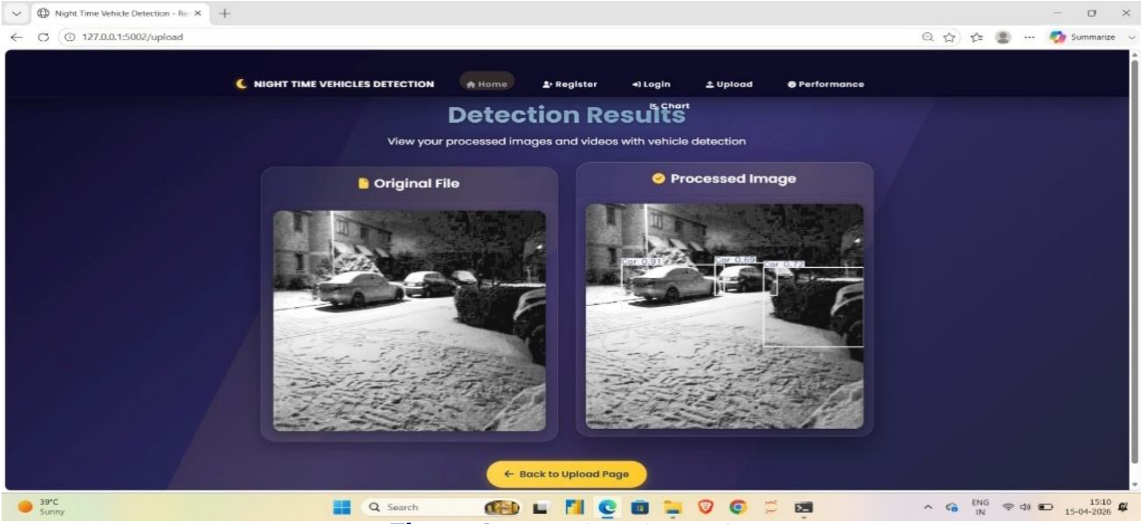

Figure 4: VERIFICATION PAGE

This page demonstrates the fingerprint liveness detection process where users upload an image and analyze whether it is real or spoofed. It displays both the original and processed results with confidence scores, ensuring accurate and secure authentication.

VII. CONCLUSION

The proposed fingerprint liveness detection system uses a lightweight YOLOv8n model to accurately distinguish between real and spoofed fingerprints. It combines efficient preprocessing, feature extraction, and classification while maintaining low computational cost. The system captures fine ridge and pore-level features, improving reliability against spoofing attacks. Its end-to-end design enables real-time performance, making it suitable for practical biometric applications. Overall, it provides a scalable and secure solution with potential for future enhancements like adaptive learning and edge optimization.

VIII. FUTURE ENHANCEMENT

In the future, the fingerprint liveness detection system can be enhanced by integrating multimodal biometrics like iris, face, or voice recognition to improve accuracy and security. It can also adopt advanced models such as transformers or VLMs to better capture complex fingerprint patterns and resist sophisticated attacks. Deploying optimized versions on edge devices like Raspberry Pi or Jetson can make the system scalable and cost-effective for real-time applications. Incorporating continuous learning methods like federated or incremental learning will help the model adapt to new spoofing techniques. Additionally, features like explainable AI and cloud-based monitoring can improve transparency, reliability, and system maintenance.

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