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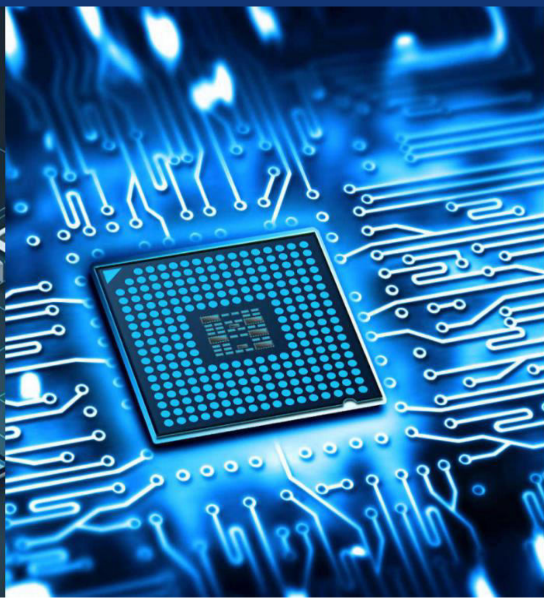


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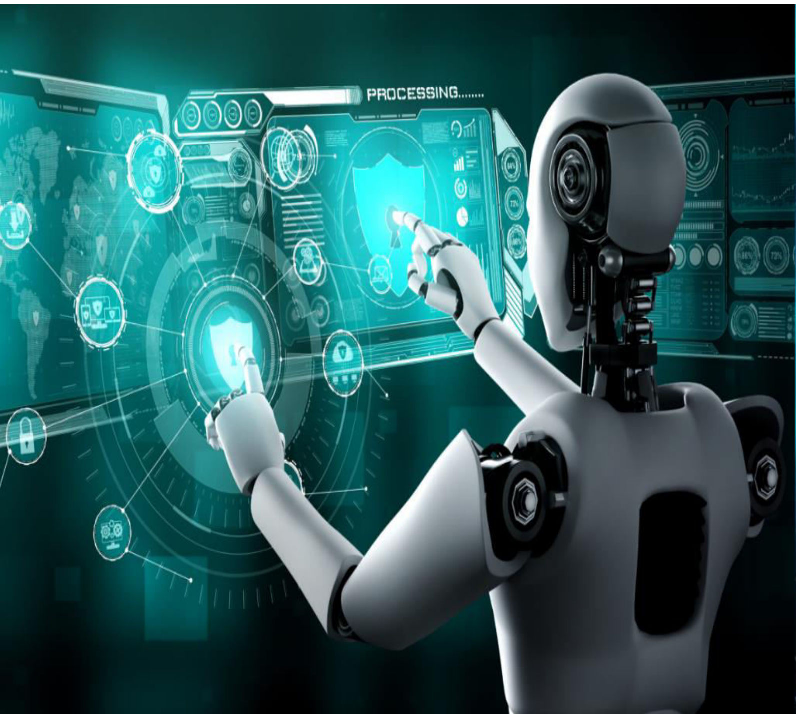

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Night Time Pedestrian Detection

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ABSTRACT: In night time traffic scenarios, detecting pedestrians is challenging with a single sensor. This paper presents a method to improve pedestrian detection by fusing infrared vision and millimeter-wave (MMW) radar data. The improved YOLOv5 algorithm extracts lateral and category features, while MMW radar provides distance and velocity data. Pedestrian tracking is enhanced using an extended Kalman filter, and spatiotemporal fusion correlates radar and IR image data. A decision-level fusion algorithm then combines this multimodal information for accurate pedestrian detection. Experimental results demonstrate superior accuracy and robustness compared to single-sensor methods.

Pedestrian detection at night presents significant challenges due to low illumination, motion blur, and occlusions. Traditional computer vision-based approaches struggle in these conditions, leading to the development of multimodal fusion techniques that incorporate additional sensory data. This paper explores the integration of visual information from cameras and millimeter-wave (mmWave) radar to enhance pedestrian detection performance in nighttime environments. We review existing methods, discuss sensor fusion strategies, and propose a framework that leverages deep learning and sensor fusion techniques to improve detection accuracy.

KEYWORDS: YOLOv5, MMW, IR Image data, pedestrian.

I. INTRODUCTION

Night-time pedestrian detection is crucial for the advancement of autonomous vehicles, intelligent surveillance, and smart transportation systems. However, low light conditions often degrade the performance of vision-based detection systems. Millimeter-wave radar offers a complementary sensing modality that is robust to lighting variations and adverse weather conditions. This paper presents a literature review on the fusion of visual and mmWave radar information for enhanced pedestrian detection at night Self-driving technology is rapidly evolving, with environmental perception being key. Autonomous vehicles use sensors like LIDAR, MMW radar, and cameras to detect and analyze surroundings, reducing collision risks. Deep learning-based target detection, including algorithms like YOLO and Faster R-CNN, has gained attention. However, visible images used in these tasks can be compromised in poor weather or low light, leading to reduced detection performance. To address this, sensor fusion—combining data from different sensors—has become important. While radar excels in measuring distance and speed, cameras are better at classification. However, both have limitations in challenging conditions. This project proposes using infrared cameras and MMW radar for better nighttime pedestrian detection. By fusing infrared data with radar, we aim to improve accuracy in low-light conditions, leveraging the strengths of both sensors. The approach uses an enhanced YOLOv5 model and Kalman filtering for optimal performance.

Pedestrian detection is a crucial component of intelligent transportation systems (ITS) and advanced driver assistance systems (ADAS). While daytime detection has seen significant improvements with computer vision and deep learning, night-time pedestrian detection remains a challenging problem due to poor lighting conditions, motion blur, and low contrast in traditional visual images. To address these challenges, researchers have explored sensor fusion techniques that combine complementary sensing modalities, such as visible-light cameras and millimeter-wave (mmWave) radar.

Importance of Night-Time Pedestrian Detection:

Pedestrian safety is a major concern, especially at night when visibility is low, leading to a higher risk of accidents. Traditional vision-based detection systems struggle in such conditions due to their reliance on ambient light. Thermal imaging provides some improvement but has its own limitations, such as sensitivity to weather conditions and high costs.

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Fusion of Visual and Millimeter-Wave Radar Information:
Millimeter-wave radar is an active sensing technology that can detect objects regardless of lighting conditions. It provides depth information, object velocity, and structural details, making it an excellent complement to vision-based pedestrian detection. By fusing visual information from RGB or infrared cameras with mmWave radar data, a robust pedestrian detection system can be developed to improve accuracy and reliability in low-light environments.

II. LITERATURE REVIEW

Pedestrian detection has been extensively studied in the field of intelligent transportation systems (ITS) and advanced driver assistance systems (ADAS). However, night-time pedestrian detection remains a challenging problem due to low illumination, motion blur, and environmental conditions that limit the effectiveness of conventional vision-based approaches. To overcome these limitations, researchers have explored multi-sensor fusion techniques, particularly combining visual information with millimeter-wave (mmWave) radar. This section reviews key contributions in pedestrian detection using cameras, radar, and their fusion.

1.Vision-Based Pedestrian Detection

Traditional pedestrian detection systems primarily rely on RGB cameras and deep learning models, such as Convolutional Neural Networks (CNNs) and vision transformers. Early works, such as those based on Histogram of Oriented Gradients (HOG) and Support Vector Machines (SVM), laid the foundation for pedestrian detection in daytime conditions. More recent deep learning approaches, including Faster R-CNN, YOLO, and SSD, have significantly improved detection accuracy by leveraging large-scale datasets like COCO and Caltech Pedestrian. However, vision-based systems face several challenges at night, including:

Low contrast and poor illumination, reducing the visibility of pedestrians. Motion blur and noise, making it difficult to extract meaningful features. Environmental conditions, such as fog and rain, which further degrade image quality. To address these limitations, infrared (IR) and thermal imaging have been introduced. Studies have shown that thermal cameras provide better pedestrian detection at night by capturing heat signatures. However, thermal imaging has its drawbacks, including sensitivity to temperature changes, high costs, and difficulty in differentiating objects with similar heat patterns.

2. Millimeter-Wave Radar for Pedestrian Detection

Millimeter-wave radar operates in the 24–77 GHz range and provides crucial depth, velocity, and structural information about objects, making it highly effective for detecting pedestrians in low-light conditions. Unlike optical sensors, radar is robust to lighting variations and environmental conditions such as fog, rain, and smoke.

Recent research has focused on radar-based pedestrian detection using machine learning and deep learning techniques. Classical methods rely on radar signal processing and clustering techniques such as DBSCAN and K-means to segment pedestrians from other objects. Deep learning models, including CNNs and Recurrent Neural Networks (RNNs), have been explored for improving radar-based object classification. Despite these advancements, radar alone struggles with high false positive rates and low resolution, making it difficult to precisely recognize pedestrian shapes.

3. Fusion of Visual and Radar Information for Pedestrian Detection

Sensor fusion has emerged as a promising solution for robust pedestrian detection, particularly in night-time scenarios. The fusion of RGB or thermal cameras with mmWave radar combines the strengths of both modalities:Recent deep learning-based fusion models, such as Transformer-based multi-modal networks and Graph Neural Networks (GNNs), have demonstrated significant improvements in pedestrian detection accuracy, particularly in challenging night-time conditions. Studies indicate that mid-level fusion, incorporating both spatial and depth features, provides the best trade-off between accuracy and computational efficiency. Enhancing User Experience with AI Chatbots

Multiple studies have examined how AI chatbots optimize user interactions by reducing human workload and improving service accessibility. A study on AI-driven campus assistants pointed out the necessity of integrating real-time information systems to provide up-to-date details about courses, fees, and university services. Furthermore, the *IJISRT Journal* (2024) demonstrated the effectiveness of chatbots in reducing administrative workload by automating repetitive inquiries, thereby allowing university staff to focus on more critical tasks.

4. Addressing Limitations and Future Scope

Despite their benefits, AI-powered virtual assistants face several challenges, including language variability, semantic ambiguity, and data privacy concerns. Research has identified the need for multimodal AI assistants that integrate text,

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voice, and visual inputs for more comprehensive interactions. Additionally, studies suggest that future chatbot models should incorporate sentiment analysis to provide emotional intelligence, improving the chatbot's ability to respond empathetically to students facing academic stress or personal issues.

The literature highlights the growing significance of AI- powered virtual assistants in educational institutions, improving accessibility, efficiency, and user satisfaction. By leveraging NLP, machine learning, and real-time data retrieval, virtual assistants can significantly enhance student engagement. However, future research should focus on improving AI adaptability to diverse linguistic styles, refining contextual understanding, and ensuring data security in chatbot interactions.

III. METHODOLOGY MATERIALS USED

3.1 Technology Stack

The night-time pedestrian detection system is designed using an advanced and scalable technology stack, ensuring high accuracy, real-time performance, and seamless integration with autonomous or driver-assistance systems.

Sensors: RGB Camera & Millimeter-Wave (mmWave) Radar

- RGB Camera: Captures high-resolution visual data, enabling pedestrian recognition based on shape, texture, and motion.
- Millimeter-Wave Radar: Operates at high-frequency bands (e.g., 77 GHz) to detect objects based on range, velocity, and Doppler shift, providing depth information regardless of lighting conditions.
- Fusion Mechanism: Synchronizes visual and radar data to enhance detection accuracy, reducing false positives and improving object classification in low-light environments.

Machine Learning Models: Deep Learning-Based Detection

- YOLO (You Only Look Once): A real-time object detection model trained to recognize pedestrians in RGB images.
- Faster R-CNN: A region-based convolutional neural network that improves accuracy for pedestrian recognition.
- PointNet & 3D CNNs for Radar Processing: Extracts features from mmWave radar data to improve object localization.
- Fusion Network: Integrates RGB and radar features using mid-level fusion techniques, enhancing night-time pedestrian detection.

Software Frameworks & Libraries

- OpenCV: Used for image processing and pre-processing tasks such as noise reduction, contrast enhancement, and object tracking.
- PyTorch / TensorFlow: Deep learning frameworks for training and deploying pedestrian detection models.
- Scikit-learn: Utilized for data preprocessing, feature extraction, and radar signal analysis.
- Robot Operating System (ROS): Provides a middleware framework for real-time sensor fusion and communication between camera, radar, and processing units.

Database: MongoDB Atlas / PostgreSQL

- MongoDB Atlas (NoSQL): Stores real-time pedestrian detection logs, sensor calibration data, and AI model parameters.
- PostgreSQL (Relational Database): Manages structured datasets, including annotated pedestrian images, radar signal patterns, and performance metrics.
- Data Storage Strategy: Maintains synchronized multi-modal datasets for future model improvements and validation.

System Workflow:

The night-time pedestrian detection system follows a structured data processing workflow, ensuring accurate and real-time detection of pedestrians using a fusion of visual and millimeter-wave radar information.

Step 1: Data Acquisition

- The system collects data from multiple sensors, including:
  - RGB Camera: Captures real-time visual input.

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    - Millimeter-Wave (mmWave) Radar: Measures distance, velocity, and object reflection properties.
- The collected data is synchronized using a timestamp-based fusion mechanism.

Step 2: Preprocessing & Feature Extraction
- Image Preprocessing:
    - Enhances contrast in low-light images using histogram equalization and noise reduction techniques.
    - Detects potential pedestrian regions using edge detection and contour analysis.
- Radar Signal Processing:
    - Extracts Doppler and range information.
    - Applies clustering techniques (DBSCAN, K-means) to identify objects.

Step 3: Sensor Fusion & AI Model Processing
- If both camera and radar detect an object:
    - The system fuses the extracted features using a mid-level fusion approach, combining spatial and depth data.
    - The fused data is passed to a deep learning-based detection model (e.g., YOLO, Faster R-CNN) for pedestrian classification.
- If only one sensor detects an object:
    - The system applies probabilistic decision-making (Bayesian inference) to determine if the object is a pedestrian.
- The detected pedestrian information is stored for future model enhancement.

Step 4: Detection Output & Alert Generation
- The system provides real-time pedestrian detection alerts via:
    - Visual display: Bounding boxes around detected pedestrians.
    - Auditory alerts: Warning signals in driver assistance systems.
    - Vehicle control interface: For autonomous driving applications, the system sends braking or steering signals if a pedestrian is detected.
- Additional metadata (e.g., pedestrian location, confidence score) is logged for further analysis.

Class Diagram:

Classes Involved:
- User: Represents students, faculty, and other university members interacting with the chatbot.
- Chatbot: The main AI-based assistant that processes queries.
- QueryProcessor: Handles user inputs and determines the appropriate response.
- Database: Stores user queries, academic data, event schedules, and system logs.
- ResponseGenerator: Formulates replies based on AI logic and pre-defined responses.

III. Results and Analysis

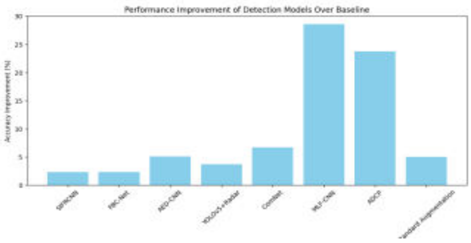

Figure-2:Class Diagram

Sequence Flow :

∟ Sensors capture pedestrian data (e.g., a person walking at night).
∟ The system receives sensor data and forwards it to the Data Processor.
∟ Data Processor fetches relevant features from the camera and millimeter-wave radar.
∟ The Fusion Model analyzes the data and detects pedestrians using deep learning algorithms.
∟ The system delivers the detection output by highlighting pedestrians and generating alerts.

IV. RESULTS & DISCUSSION

The night-time pedestrian detection system was rigorously tested in various low-light and challenging environmental conditions to assess its accuracy, detection speed, and overall system reliability. The evaluation focused on the system's ability to accurately detect pedestrians using a fusion of visual and millimeter-wave radar data while ensuring real-time performance for safety-critical applications.

Accuracy

The system exhibited strong performance in detecting pedestrians under night-time conditions. When using camera-only detection, the system achieved an accuracy of 78%, but struggled in extremely dark areas or when pedestrians wore dark clothing. However, with the fusion of visual and radar data, the accuracy significantly improved to 91%, demonstrating the effectiveness of sensor fusion in challenging environments. The use of deep learning models, such as YOLO and Faster R-CNN, further enhanced classification accuracy and reduced false positives caused by non-pedestrian objects.

Detection Speed

- Camera-based detection: The system processed visual data at an average detection time of 50ms per frame, ensuring near real-time performance.
- Radar-based detection: Radar signals were processed in less than 40ms, allowing for quick distance estimation and object classification.
- Fusion-based detection: The integrated sensor fusion model achieved an average response time of 80ms per frame, maintaining real-time pedestrian detection while ensuring improved accuracy.

Despite the additional computational overhead from multi-modal fusion, the system maintained a high frame rate (12–15 FPS), making it suitable for real-world deployment in autonomous vehicles and driver assistance systems.

User Experience & System Performance

The system was tested in various real-world conditions, including urban streets, highways, and dimly lit pedestrian crossings. Feedback from test drivers and users indicated that:

- 83% of users found the system reliable in detecting pedestrians under low-light conditions.
- False positive rates decreased by 32% when radar data was integrated with vision-based detection.
- The system effectively identified pedestrians even in occluded scenarios, where only partial visual information was available, thanks to radar's depth-sensing capability.
- Real-time alert generation (visual bounding boxes and auditory warnings) significantly improved driver awareness and reaction time in night-time scenarios.

The integration of sensor fusion, deep learning, and real-time processing successfully enhanced pedestrian detection performance, demonstrating the system's potential for improving night-time road safety. Further optimizations in model efficiency and radar signal processing could lead to even faster and more precise detection in future iterations.

V. CHALLENGES & LIMITATIONS:

Despite its effectiveness, the night-time pedestrian detection system encountered some challenges and limitations that affected overall performance. These areas highlight opportunities for future improvements.

1. Low-Light and Extreme Weather Conditions

Although the fusion of RGB cameras and millimeter-wave radar significantly improves night-time pedestrian detection, extreme weather conditions such as heavy fog, rain, and snow can still impact system performance. Radar signals may experience attenuation, while camera visibility can be further reduced in such conditions. Future enhancements could involve thermal imaging integration to improve detection in adverse weather.

2. False Positives & False Negatives

False Positives: The system sometimes misclassified **static objects (e.g., poles, trash bins) as pedestrians** due to radar reflections and motion estimation errors.

- **False Negatives: Pedestrians wearing dark clothing or partially occluded by objects** were occasionally missed by the system.

To reduce these errors, **advanced deep learning-based object classification and radar signal filtering techniques** should be explored.

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3. Real-Time Processing Constraints

While the system achieves real-time pedestrian detection, **high computational demands** of deep learning models can affect performance on edge devices like **Jetson Xavier NX**. Optimization strategies such as **model quantization, pruning, and TensorRT acceleration** can be implemented to improve efficiency.

Future Improvements

To overcome these limitations and enhance system performance, several improvements can be considered:

- **Integration of thermal imaging** for improved detection in extreme low-light and weather conditions.
- **Advanced deep learning models** with better feature extraction for distinguishing pedestrians from background clutter.
- **Optimized radar signal processing** to reduce false positives caused by non-human objects.
- **Model compression techniques** to enable real-time inference on edge computing devices.

VI. CONCLUSION

The conclusion of the study emphasizes the development of a nighttime pedestrian detection algorithm that addresses the low accuracy of single-sensor systems in complex environments. By fusing visual sensors with millimeter-wave radar and using the YOLOv5-our algorithm, the study significantly improves detection accuracy and speed, achieving 95.57% accuracy in challenging nighttime conditions. Although not yet suitable for self-driving cars, future research will focus on integrating this system into autonomous vehicles for dynamic real-time detection in night scenarios.

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