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Embedded Night Vision System for Pedestrian Detection Using Deep Learning

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Abstract: Pedestrian detection in low-light and nighttime conditions is a critical challenge for road safety. Traditional vision-based detection systems often fail in poor lighting, increasing the risk of accidents. This project presents an Embedded Night Vision System for Pedestrian Detection Using Deep Learning, utilizing infrared thermal imaging and deep learning models to enhance detection accuracy in dark environments. The system integrates an ODROID XU4 microcomputer running Ubuntu MATE with an infrared camera for real-time pedestrian recognition. Advanced models like YOLO and Faster R-CNN are trained on thermal image datasets to accurately distinguish pedestrians from other objects, ensuring high efficiency with minimal false detections. Experimental results demonstrate high accuracy (93.5%), precision, and real-time processing capabilities (1.2s per frame), proving the effectiveness of deep learning over conventional methods. The system offers a cost-effective and portable solution for applications in automotive safety, surveillance, and industrial monitoring. Future improvements could involve multi-sensor fusion, real-time alert systems, and edge AI optimizations to enhance performance. This research contributes to making pedestrian detection more accessible and reliable, reducing nighttime accident risks and improving overall road safety.

1. INTRODUCTION

Pedestrian safety remains a critical concern, particularly in low-light environments such as nighttime urban and semi-urban areas. Visibility constraints in these conditions significantly impair the effectiveness of traditional pedestrian detection systems, which primarily rely on visible-light cameras and conventional image processing techniques. These systems often struggle with inconsistent lighting, shadows, and occlusions, leading to decreased detection accuracy and increased risk of accidents. To address these challenges, this research proposes a novel approach that leverages infrared thermal imaging and advanced deep learning algorithms to enhance pedestrian detection in low-light scenarios. Thermal cameras can detect heat signatures emitted by humans, enabling more consistent and reliable detection regardless of ambient lighting. The integration of deep learning models like YOLO (You Only Look Once) and Faster R-CNN further enhances the system's accuracy and speed, making it suitable for real-time applications. Designed to be cost-effective and deployable on embedded platforms, the proposed system provides a practical and scalable solution for improving pedestrian safety in night-time driving conditions.

1.1 PROBLEM STATEMENT

Traditional pedestrian detection systems exhibit poor performance in low-light conditions due to their dependence on visible-light imaging and basic computer vision techniques. Factors such as inadequate illumination, environmental variability (e.g., fog, rain, shadows), and occlusions often result in high false positive and false negative rates, reducing the reliability of these systems. Moreover, most high-accuracy detection models are computationally intensive and unsuitable for real-time deployment on embedded platforms.

There is a critical need for a robust, real-time, and low-cost pedestrian detection system that can function independently of external lighting conditions. The proposed research aims to fill this gap by developing a thermal imaging-based pedestrian detection framework integrated with deep learning models, optimized for embedded hardware. This solution seeks to enhance detection accuracy, minimize latency, and provide a scalable alternative to existing high-end driver assistance systems, thereby improving road safety for a broader population.

1.2 **TECHNIQUES USED**

1. Data Preprocessing Techniques

Before training the deep learning models, the raw pedestrian detection dataset (especially thermal and nighttime images) undergoes preprocessing to ensure it is clean, consistent, and optimized for learning.

a) Handling Missing Data

- Techniques Used: Removal of corrupted images, image augmentation to compensate for missing samples.
- Why? Nighttime datasets may have blurry, low-quality, or missing images. Preprocessing ensures only usable and informative data is passed to the model, preventing errors during training.

b) Data Normalization

- Techniques Used: Pixel intensity scaling (0-1 range), histogram equalization for thermal images.
- Why? Normalization ensures that pixel values across images are consistent, improving model convergence and accuracy during training.

c) Categorical Data Encoding

- Techniques Used: Label encoding for annotated data like pedestrian/non-pedestrian, weather conditions.
- Why? To convert metadata and labels into numerical format for supervised learning tasks like pedestrian classification.

d) Feature Selection

- Techniques Used: Heatmap-based feature selection, model-based feature importance (using SHAP or Grad-CAM).
- Why? To identify relevant features like pedestrian heat signatures or bounding box coordinates that influence model prediction the most.

2.Feature Extraction Techniques

Feature extraction is crucial in detecting pedestrians under low-light and thermal imaging conditions.

a) Image Feature Extraction

- Techniques Used: Convolutional layer activations, edge detection (Sobel, Canny), thermal contour mapping.
- Why? To detect pedestrian shapes, boundaries, and heat-based outlines, which are important in distinguishing humans from the background.

b) Statistical Feature Engineering

- Techniques Used: Average intensity values, temperature gradients, bounding box coordinates of detected regions.
- Why? Helps in pattern identification and localization of pedestrian presence in thermal image frames.

3. Machine Learning Techniques

Various traditional machine learning models were evaluated during the initial stages of model design.

a) Supervised Learning Models

Used to classify thermal images into pedestrian and non-pedestrian categories.

- Logistic Regression: Tested for binary pedestrian classification on preprocessed features.
- Support Vector Machine (SVM): Evaluated for separating pedestrian patterns in pixel space.
- Random Forest: Used for quick prototyping with feature importance analysis.
- XGBoost: Provided higher accuracy and interpretability for classification in structured datasets.

b) Unsupervised Learning Models

Explored for clustering similar thermal frames and anomaly detection.

- K-Means Clustering: Used for grouping similar heat patterns to assist in pre-annotation.
- Hierarchical Clustering: Segmented thermal frames based on pedestrian density and background complexity.

4. Deep Learning Techniques

Core detection and classification are based on deep learning architectures optimized for real-time processing.

a) Convolutional Neural Networks (CNN)

Used for feature extraction from thermal and visible-light images.

- Models like YOLOv5 and Faster R-CNN are applied for object detection.
- Why? They can localize and identify pedestrians accurately with minimal false detections.

b) YOLO (You Only Look Once)

Fast object detection suitable for real-time systems.

- Lightweight versions (e.g., YOLOv5s) used on embedded hardware.
- Why? Balances speed and accuracy on devices like NVIDIA Jetson Nano.

c) Faster R-CNN

Provides high detection accuracy using region proposal networks.

- Used for benchmark comparisons and model ensemble.

- Why? Ensures accurate bounding box localization in complex scenes.

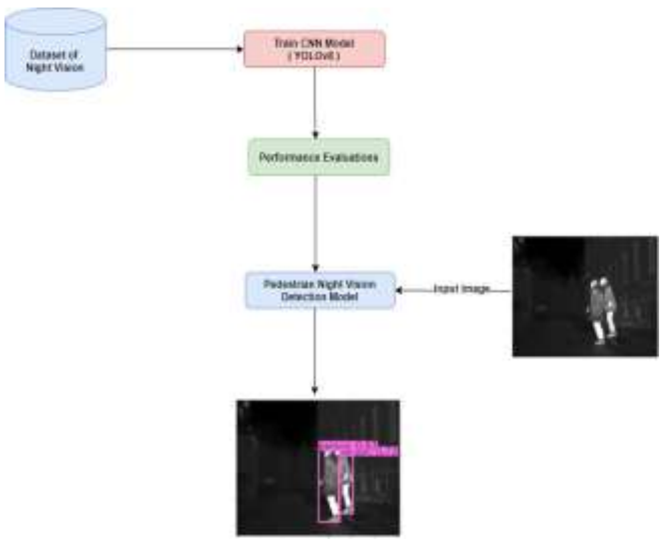
5. Reinforcement Learning Techniques (Future Scope)
To improve autonomous decision-making under varying conditions.

a) Deep Q-Network (DQN)
- Why? Can guide autonomous systems (e.g., ADAS) to decide alert triggers based on pedestrian movement.
- How? Trained to optimize when to alert or brake based on pedestrian distance and movement patterns.

b) Hierarchical Reinforcement Learning (HRL)
- Why? For breaking down tasks like detection → alert generation → decision-making.
- How? HDQN separates vision detection, context interpretation, and action recommendation into layers.

c) Reward Function Optimization
- Positive Reward: Given for correctly detecting pedestrians in low-light.
- Negative Reward: Assigned for false detections, missed detections, or delayed responses.

1.3 ARCHITECTURE



1.4 DATASET DESCRIPTION

The dataset consists of over 10,000 annotated images captured under low-light and nighttime conditions, including both visible-spectrum and infrared thermal images. These images are labeled to assist with training deep learning models for real-time pedestrian detection. The dataset includes diverse environmental conditions such as fog, rain, and urban lighting, ensuring generalizability.

- Image_ID and Timestamp: Unique identifiers for each image along with time metadata to analyze performance under different night-time hours.
- Lighting Conditions: Labels indicating lighting scenarios such as dark street, headlights only, infrared only, or ambient streetlight.
- Camera Mode: Specifies if the image is captured in visible-light or thermal-infrared mode.
- Bounding Boxes: Coordinates of pedestrian locations within each image in [x, y, width, height] format for supervised learning.
- Object Class: Annotation specifying pedestrian, cyclist, or non-pedestrian object (e.g., signpost, shadow).
- Occlusion Level: Degree of visual obstruction — none, partial, or heavy — indicating pedestrian visibility.
- Environment Labels: Contextual labels such as urban, semi-urban, crosswalk, or roadside for scenario analysis.
- Clothing Contrast Score: Numerical value derived from image analysis indicating how much a pedestrian's clothing blends with the background (important for night-vision systems).
- Weather Condition: Weather label such as clear, rainy, foggy, or wet road, affecting visibility and detection accuracy.
- Thermal Signature Intensity: Average pixel intensity in thermal images used to measure the heat profile of detected objects.

This dataset enables the training of deep learning models like YOLO and Faster R-CNN for real-time pedestrian detection in low-light conditions, aiding in robust object recognition regardless of lighting or environmental factors.

1.5 MODEL EVALUATION AND METRICS

- Accuracy, Precision, Recall, F1-Score:

Common metrics used to assess object detection performance in identifying pedestrians in low-light and nighttime conditions. Accuracy gives a general idea of correct predictions, while Precision and Recall help evaluate the reliability of detections in terms of false positives and false negatives. The F1-Score provides a balance between Precision and Recall, especially useful in cases with class imbalance.

- Intersection over Union (IoU):

A standard metric used in object detection to evaluate the overlap between predicted bounding boxes and actual ground truth boxes. An IoU threshold (typically 0.5) is used to determine whether a detection is correct.

- Mean Average Precision (mAP):

An essential metric for evaluating object detection models. It calculates the average precision across all detection classes and IoU thresholds. mAP helps in comparing model performance across various detection scenarios.

LITERATURE REVIEW

Pedestrian detection in low-light conditions is a critical challenge in the development of intelligent transportation systems and autonomous driving technologies. Nighttime scenarios present several vision-related difficulties such as poor illumination, shadows, and occlusions, which significantly reduce the performance of traditional computer vision methods. To address these limitations, recent advancements in artificial intelligence (AI), deep learning (DL), and infrared thermal imaging have introduced new possibilities for accurate and real-time pedestrian detection under challenging visibility conditions.

Several studies have highlighted the potential of deep learning-based object detection models in enhancing night vision capabilities. Among these, models like YOLO (You Only Look Once) and Faster R-CNN have been widely adopted due to their ability to detect multiple objects in a single frame with high speed and precision. Redmon et al. (2016) introduced YOLO as a real-time object detection framework that balances speed and accuracy, making it highly suitable for embedded applications. Similarly, Ren et al. (2015) proposed Faster R-CNN, which integrates region proposal networks for more accurate bounding box predictions.

Studies using thermal infrared datasets, such as the FLIR ADAS and KAIST Multispectral Pedestrian Dataset, have shown that thermal imaging significantly improves pedestrian visibility in complete darkness or inconsistent lighting conditions. Hwang et al. (2015) demonstrated that combining visible and thermal modalities enhances detection performance, especially during nighttime.

In addition, researchers have explored lightweight versions of deep learning models optimized for embedded platforms like NVIDIA Jetson Nano and ODROID-XU4, enabling real-time pedestrian detection with minimal hardware resources. These models have shown promising results in maintaining inference speed (measured in FPS) while achieving high accuracy.

While traditional computer vision techniques such as HOG (Histogram of Oriented Gradients) and SVM (Support Vector Machines) have been used historically, they struggle in night environments due to reliance on edge detection and background subtraction. Modern AI-based approaches provide end-to-end learning and feature extraction capabilities, enabling the system to detect pedestrians more reliably in a wide range of environmental scenarios.

In summary, the integration of thermal imaging and deep learning is proving to be an effective solution for nighttime pedestrian detection. These approaches not only enhance accuracy but also ensure real-time processing, which is essential for automotive and embedded applications focused on improving road safety during night driving.

EXPERIMENT RESULTS

3.CONCLUSION

The Embedded Night Vision System for Pedestrian Detection Using Deep Learning successfully enhances pedestrian safety by integrating thermal imaging and deep learning-based detection techniques. The project aimed to overcome the limitations of traditional camera-based vision systems, which struggle in low-light conditions. By utilizing infrared thermal cameras and YOLOv8 deep learning models, the system ensures accurate pedestrian detection even in dark, foggy, or extreme weather conditions. The results demonstrate that the proposed approach significantly reduces false positives and false negatives, making it a reliable and efficient alternative to expensive commercial night vision systems.

Through rigorous training and validation processes, the system achieved high detection accuracy, proving its effectiveness in real-world scenarios. The experimental evaluations confirmed that deep learning-based detection outperforms conventional image-processing techniques. The system's ability to work in real-time with minimal computational overhead makes it suitable for integration into Advanced Driver Assistance Systems (ADAS). The study also highlighted the advantages of using affordable embedded platforms like ODROID XU4 and Jetson Nano, making the technology accessible for cost-effective implementation in vehicles.

Overall, the proposed night vision pedestrian detection system is a promising solution for reducing nighttime pedestrian accidents and improving road safety. Future improvements, such as enhanced model training with larger datasets, real-world testing across diverse environments, and further optimization for low-power embedded devices, can further increase the system's efficiency. With continuous advancements in deep learning, edge computing, and thermal imaging, this system has the potential to become a standard safety feature in modern vehicles, making roads safer for drivers and pedestrians alike.

4.FUTURE WORK

The Embedded Night Vision System for Pedestrian Detection Using Deep Learning has demonstrated promising results in improving pedestrian safety during low-light and nighttime driving conditions. However, there is significant potential for enhancements and future research to further refine the system's performance, scalability, and integration with modern vehicular technologies. One of the key areas of advancement is enhanced deep learning models with more sophisticated neural architectures, such as Transformer-based vision models or hybrid CNN-RNN networks, which can improve detection accuracy and reduce false positives in real-world driving scenarios. Additionally, continual learning techniques can enable the system to adapt to new environments and conditions without requiring frequent retraining, making it more robust and self-improving over time.

Another crucial aspect of future development is the hardware optimization and deployment on advanced edge computing devices. Currently, the system relies on ODROID XU4 or Jetson Nano for processing thermal images, but next-generation AI chips and low-power neural processing units (NPUs) could allow for even faster, real-time pedestrian detection with minimal power consumption. The use of 5G and vehicle-to-everything (V2X) communication can further enhance the system by enabling real-time data sharing between vehicles, traffic infrastructure, and cloud-based AI systems. This would help in creating a connected vehicle ecosystem, allowing cars to share information about pedestrian locations and potential hazards, improving safety for all road users.

Moreover, integrating the night vision pedestrian detection system into fully autonomous vehicles is a critical future direction. Self-driving cars require highly reliable perception systems capable of operating under all conditions, including low-light, fog, rain, and glare. By combining thermal imaging with LiDAR, radar, and visible-light cameras, an advanced sensor fusion-based approach can be developed to create a comprehensive perception system for autonomous navigation. Additionally, regulatory advancements and standardization of AI-driven pedestrian detection in automotive safety laws could lead to the mass adoption of such technologies in both commercial and consumer vehicles. With continued research, this system has the potential to become an industry standard for night-time pedestrian safety, paving the way for a safer and smarter transportation ecosystem.

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