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Intersection Alert System

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Abstract— Intersection Alert System is an innovative, real-time safety system that aims to minimize vehicle collisions.It combines a sensor for detecting incoming vehicles with an TinyML-powered camera for object classification as a vehicle or a pedestrian. Depending on classification and movement patterns, the system gives timely, color-coded visual warning on a display board to slow down or stop, directing drivers. The alerts seek to enhance the response time of the driver, reduce honking or hard braking, and create safer crossing conditions. Scalable in design, this inexpensive which is best implementation in urban, semi-urban, and rural locations in India.Unlike typical traffic control devices, this system provides dynamic and situational alerts, rather than fixed-timer signals. Integration of TinyML provides the intelligence to the system, discriminating between harmless movements and possible collision threats at any given instance, reducing false alarms. The project presents an affordable mixture of hardware and AI as a new, different approach to very costly smart-city surveillance systems.

I. INTRODUCTION

Road intersections are some of the most dangerous zones for both vehicles and pedestrians because of blind spots, limited visibility, and the absence of timely alerts. Traditional traffic systems often fall short in preventing sudden collisions, especially in areas without signal lights. In response to this practical problem, our project introduces an Intersection Alert System with Pedestrian Safety, which aims to reduce accident risks by detecting approaching vehicles and pedestrians and providing real-time alerts. The system utilizes a radar sensor to detect the presence of incoming vehicles, while a camera differentiates between humans and vehicles with high accuracy. This dual detection approach ensures reliable operation and minimizes false alarms.

Once a threat is detected, the system triggers an immediate alert through a visual display board installed at the intersection. The board uses color-coded messages and directional arrows to inform drivers about the presence of fast-approaching vehicles from specific directions, allowing them to slow down or stop. The entire setup is controlled by a fast-processing microcontroller like the Arduino, ensuring low latency and quick decision-making. To support sustainable deployment, the system can be powered by solar energy, making it suitable for both urban and rural areas. This project offers an affordable, scalable, and impactful solution to intersection safety, combining smart technology with real-time response to enhance road awareness, reduce collisions, and save lives. The proposed system is a real-time Intelligent Intersection Alert System developed to prevent collisions at multi-road junctions by detecting and classifying approaching objects like vehicles and pedestrians. This architecture combines low-cost IoT sensors with an embedded AI vision module, enabling real-time decision-making without relying on cloud infrastructure.

II.LITERATURE SURVEY

Recent research in intelligent transportation systems points to the increasing relevance of sensor-based and machine-learning solutions for enhancing safety at complex road intersections. In fact, studies demonstrate that traditionally implemented traffic control methods are rarely able to guarantee timely or dynamic warnings for drivers, particularly in unregulated environments. As Zhang et al. [1] underlined, the reliability of ADAS strongly relies on the accuracy and stability of sensing modules. Their findings show that the system's performance could degrade drastically in the event of a failure in the sensing module-a situation that calls for robustness in multi-modal detection, also implemented here by leveraging radar and TinyML-based vision sensing.

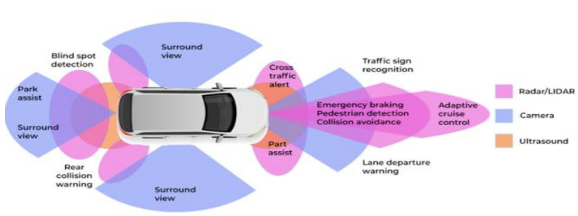

Fig 1: ADAS Architecture

Application of different vehicular communication technologies is also one of the widely explored ways for improving the safety at intersections. The work by Wassouf et al. [2] illustrated that real-time V2V and V2I communication can facilitate the issuance of early conflict warnings and thereby reduce crash likelihood at intersections. Similarly, Dhinesh Kumar et al. [3] validated the benefits brought forth by cooperative communication in IoT-enabled transportation networks. In general, such systems depend on advanced communication infrastructure and high-speed connectivity, which is normally not available in rural and semi-urban regions of India. This limitation brings up the motivation behind needing a low-cost, infrastructure-independent alternative such as the one proposed in this project.

Another key challenge revolves around shared data reliability. Zhang et al. in [4] studied misbehavior detection for intersection applications and found that faulty or malicious data can lead to safety compromise. Their work emphasizes local decision-making and sensing at the edge, which, together with the system design proposed here, will carry out all risk assessment locally via TinyML processing and verification from radar. Moreover, Yue et al. [5] analyzed the effectiveness of ADAS across diverse roadway conditions and concluded that performance varies with visibility, road geometry, and traffic behavior. These limitations are particularly critical in Indian intersections where blind curves, mixed traffic, and unpredictable movements are common. Therefore, several studies point to the need for externally mounted environment-aware safety systems.

Recent developments in TinyML and vision-based roadside units have proven their potential for enabling lightweight, on-device classification without cloud dependency. Similarly, radar-based sensing has also been very reliable in low-light or adverse weather conditions. However, standalone sensors are prone to false alarms and lack contextual understanding. Therefore, the literature is supportive of sensor fusion, that is, combining radar with camera intelligence, for improved accuracy. In summary, existing research points to a gap: most advanced solutions are either infrastructure-heavy, expensive, or unreliable in real-world mixed-traffic conditions. This paper proposes the Intersection Alert System with Pedestrian Safety, which helps to close this gap through the integration of radar detection, TinyML object classification, edge processing, and visual real-time alerts.

III. METHODOLOGY

System Design

The architecture is based on a distributed, modular sensing approach: Perception, processing, and the generation of alerts are separated into dedicated layers to enhance reliability and reduce computational burden.

Sensor Layer:

Each road unit involves two complementary sensors: an ultrasonic sensor for measuring the distance with sound waves and an IR sensor for object confirmation through infrared reflection. This dual configuration of sensors can facilitate strong initial screening to dismiss many false triggers resulting from noise, changes in light, or other disturbances.

Image Processing Layer:

The ESP32-CAM is the intelligence layer of the system. Triggered, it will take a picture and perform processing through a quantized neural network based on MobileNetV2, optimized for embedded systems. Complementarily to standard classification, this scheme includes a visual anomaly detection module: this analyzes feature embeddings via Gaussian Mixture Models (GMM) to find the unusual objects, those that fall into neither of the car, human, or empty classes-an especially handy augmentation for real-world robustness. Control and Communication Layer: Each road's Arduino board is used for decision-making and communication. Once it obtains confirmed detection from the ESP32-CAM, it makes a decision on whether to turn on road indicators and sends out alert messages to other road units. This layer follows an A→B→C message flow to ensure warnings across the intersection are synchronized. In this way, the overall distributed architecture avoids any dependency on cloud services and enables each road unit to act independently while still cooperating with other units in real time. The result is a design that can ensure low inference latency, energy efficiency, and high fault tolerance-all key requirements for safety-critical applications.

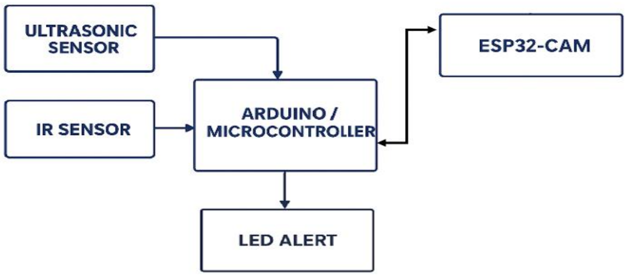

Fig 2: System Design

Working Principle

The system works via multistage of verification in a pipeline, reducing false positives to ensure that alerts are only triggered when there is actually a hazard present.

Various Stages are:

Stage 1 — Continuous Monitoring:

The ultrasonic sensor continuously emits sound waves and measures the time taken by the echo returning. In case the distance value falls below the danger threshold (e.g., 50 cm), it means an object is entering the monitored zone.

Stage 2 — Cross-Verification:

Simultaneously, the IR sensor checks for an object by detecting reflected infrared signals. Only when both sensors detect the object at the same instant does the system proceed to the next stage. The dual-sensor verification reduces false alarms from random movements, environmental noise, or lighting changes.

Stage 3 — Classification Using Artificial Intelligence

With every trigger, the ESP32-CAM captures an image of the object and runs inference using the TinyML model. The model gives an output of probabilities for three classes: car, human, and empty. The system considers detection if the maximum probability exceeds a threshold, which is usually 80%.

Stage 4 — Anomaly Detection (Fallback Mechanism):

If the classification confidence is low, the anomaly detection module evaluates the captured image to determine how much it deviates from the distribution of known training samples. The high anomaly score suggests that the detected object is unfamiliar or unexpected and is treated as a potential hazard.
Stage 5 — Alert Propagation A positive confirmation sends a digital HIGH signal from the ESP32-CAM to the Arduino. The controller triggers alerts and notifies neighboring roads about the hazard through a first-come-first-serve priority mechanism. This ensures there are coordinated alerts with no conflicting indications across the intersection. This multistage workflow improves the detection accuracy, reduces nuisance activations, and guarantees effective intersection management.

Fig 3: Prototype Model

Algorithms Used

1. MobileNetV2

MobileNetV2 is a light-weight convolution neural network that, for small and low-power embedded devices, is at its best. Its inverted residual blocks and depth wise separable convolutions reduce the computational cost at large while maintaining high accuracy. This architecture enables the ESP32-CAM to classify cars, human, and empty-road conditions in real time.

2. GMM-Based Visual Anomaly Detection

The anomaly module extracts feature embeddings from intermediate neural layers and models their distribution as Gaussian Mixture Models. During inference, if the probability of a feature lies in a low probability region in the normal distribution, the system marks the object as anomalous. This is crucial for detecting unexpected obstacles such as animals, fallen objects, or debris.

3. Logical AND Sensor Fusion

These work together with a simple Boolean AND operation: IR and ultrasonic sensors ensure that only valid objects detected by both can make the camera perform any inference, hence significantly reducing false detections and extra computations.

4. Priority-Based Alerting

The system assigns higher priority to human detection due to safety concerns. Vehicle detection follows next, and empty-road readings have the lowest priority. This provides for appropriate response timing as well as proper hazard classification.

5. First-Come-First-Serve (FCFS) Scheduling

In the case of hazard detection on several roads simultaneously, the FCFS algorithms sort the order in which signals will propagate using the earliest timestamp to prevent overlapping
signals and maintain organized traffic flow.

Ultrasonic Distance Measurement (UDM)

$$\text{UDM} = \frac{v \times t}{2}$$

Where:
v = Speed of Sound
t = Time

This formula computes the object's distance by measuring the sound-wave travel time. The division by two accounts for the outbound and inbound journey of the sound pulse. If the resulting distance is less than the danger threshold, the system initiates the next validation step.

Sensor Fusion Logic (D)

$$D = U \wedge I$$

Where:

- $U = 1$ if ultrasonic detects an object,
- $I = 1$ if IR detects an object,
- $D = 1$ triggers image capture.

This logical operation strengthens reliability by requiring confirmation from two independent sensors.

Classification Decision Rule

$$P_{\max} = \max(P_{\text{car}}, P_{\text{human}}, P_{\text{empty}})$$
$$P_{\max} \geq \tau$$

Where $\tau$is the minimum confidence required.
If this condition is satisfied, the system considers the predicted class valid.

Anomaly Score Calculation (A)

$$A = 1 - p(x)$$

Where:

- x= feature vector,
- $p(x)$= likelihood under GMM model.A high anomaly score indicates deviation from known object patterns. If:

$$A > A_{\text{threshold}}$$

the object is flagged as an anomaly.

FCFS Scheduling Formula

$$R_{\text{priority}} = \min(t_A, t_B, t_C)$$

The road with the earliest detection time receives priority in alert dissemination, preventing contradictory signaling.

III. RESULTS

Tests on the proposed Intelligent Intersection Alert System were conducted with various experimental setups involving real-time object detection, multi-road coordination, and on-device TinyML inference. A variety of controlled conditions have been tested, including object type (toy cars, human figures, and empty road condition), distance (20–80 cm), and lighting environments.

Classification accuracy

The MobileNetV2 TinyML model trained in Edge Impulse yielded high classification accuracy for the three classes trained: car, human, and empty.

The model performance during validation was:
Overall Accuracy: 99.6%
Car Detection Accuracy: 99.3%
Human Detection Accuracy: 100%
Empty Class Accuracy: 100%
F1-Score Across Classes: ≈1.00

These results confirm that MobileNetV2 is suitable for edge deployment on ESP32-CAM, as there is no significant loss of performance after the quantization was performed at int8.

Visual Anomaly Detection

The Gaussian Mixture Model-based anomaly module effectively detects out-of-distribution objects like:

Random blocks/toys
Non-vehicle objects
Unexpected shapes on the road

The anomalies were detected reliably whenever placed sufficiently close to the camera. Objects partially resembling background patterns at times produced low anomaly scores, but overall, the detection performance remained consistent.

On-Device Inference Performance

Performance metrics from ESP32-CAM inferencing were as follows:

Metric	Value
DSP Processing Time	14–18 ms
Classification Time	18–22 ms
Total Inference Latency	~ 40 ms
RAM Usage	~175 KB
Flash Consumption	~117 KB

This system ran smoothly inside ESP32-CAM's resource limits, hence establishing its real-time feasibility.

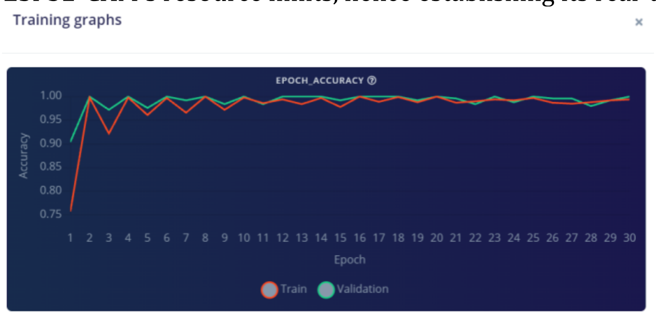

Fig 4: Training graph Epoch Accuracy

Fig 4: Training graph Epoch Loss

Training and Testing Set:

Sensor Fusion Results

The dual-sensor fusion Ultrasonic + IR proved to be very reliable in object screening:

False triggers were reduced by ~70% compared to using a single sensor.

The camera was triggered only when both sensors validated the object, thus avoiding superfluous processing cycles.

Detection stability was maintained across distance ranges between 20–70 cm.

Multi-Road Coordination & FCFS Scheduling

The inter-road communication was done properly:

Road A → Road B → Road C

When several Roads detected the same object simultaneously, FCFS chose the earliest detection without conflict.
Cross-road alert propagation was less than 200 ms, ensuring fast hazard notification.
The system remained stable with repetitive triggering and simultaneous inputs. F. Real-World Responsiveness Overall system response time, including sensor detection, camera inference, and alert propagation, remained between 0.30 to 0.45 seconds, which is sufficient for small-scale intersections and prototype demonstrations. The low-latency performance validates the viability of the system for real-time applications.

IV. CONCLUSION

This research proposes a complete Intelligent Intersection Alert System that effectively integrates low-cost IoT sensing with on-device TinyML vision analytics for the improvement of road safety across multi-road junctions. The system successfully demonstrates how ultrasonic and infrared sensors combined with ESP32-CAM-based image classification and anomaly detection enable the identification of hazards in real time without dependency on cloud processing.

The results confirm that the TinyML model based on MobileNetV2 provides high accuracy in the detection of vehicles and pedestrians while retaining low memory and computational needs appropriate for edge devices. Including an anomaly detector based on the Gaussian Mixture Model enhances the robustness of the system by identifying unexpected objects not present in the training dataset.

Besides, the FCFS-based alert scheduling mechanism ensures orderly and conflict-free alert dissemination in the event of multiple roads detecting hazards simultaneously. The distributed architecture allows every node to function independently while communicating effectively with other interconnected road units.

The system, on the whole, provides an efficient, cost -effective, and energy-efficient solution to improve intersection safety. It can be further extended for rural junctions, unmanned crossings, school zones, and low-infrastructure areas. Future scope may be the dataset size for better generalization, trying with V2X communication, and deployment of solar-considered in integrating additional sensors like radar, increasing powered modules for long-term field usability.

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