MICRO VISION KIT: AI-DRIVEN OBJECT DETECTION FOR IOT APPLICATIONS

Ms. Yuvamaliga B.M

Assistant Professor,

Department of Electronics and Communication Engineering
T.J.S. Engineering College,
Chennai, India
yuvamaligamalliga@gmail.com

Nissi Jerusha K
Department of Electronics and Communication Engineering
T.J.S. Engineering College,
Chennai, India
nissijerusha333@gmail.com

Nishanthini V
Department of Electronics and Communication Engineering
T.J.S. Engineering College,
Chennai, India
nisha65769@gmail.com

Swetha Reddy J
Department of Electronics and Communication Engineering
T.J.S. Engineering College,
Chennai, India
prathapswethareddy@gmail.com

Pushpalatha T
Department of Electronics and Communication Engineering
T.J.S. Engineering College,
Chennai, India
pushpamoorthi.pm@gmail.com

ABSTRACT

The evolution of edge computing and artificial intelligence (AI) has enabled the development of compact, efficient, and real-time intelligent systems for Internet of Things (IoT) applications. This project presents a Micro Vision Kit, a lightweight, AI-driven object detection system designed for integration into IoT ecosystems. Utilizing deep learning models such as YOLO (You Only Look Once) or Mobile internet SSD, the kit performs real-time object recognition on edge devices like Raspberry Pi or ESP32-CAM, significantly reducing latency and the need for continuous cloud communication. The system supports wireless data transmission to cloud platforms for further analysis and remote monitoring, making it highly suitable for smart surveillance, industrial automation, and smart home applications. Emphasis is placed on achieving high detection accuracy while maintaining low power consumption and cost-effectiveness. The proposed Micro Vision Kit demonstrates the potential of edge-AI in decentralizing intelligence and enhancing the efficiency and responsiveness of IoT-enabled environments.

Keywords —

Edge Computing, Object Detection, IoT, Deep Learning, Raspberry Pi, YOLO, Real-Time Vision, AI on Edge

I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) and the Internet of Things (IoT) has paved the way for the development of intelligent and autonomous systems capable of real-time decision-making. Among these, object detection systems have become essential in applications requiring enhanced surveillance, automation, and operational efficiency. From industrial monitoring to smart cities and healthcare, the demand for accurate and fast object detection has significantly increased.

This project, titled **"Micro Vision Kit: AI-Driven Object Detection for IoT Applications,"** presents a compact and scalable solution that integrates edge computing with machine learning algorithms to detect and classify objects in real time. By leveraging models like YOLO (You Only Look Once) or Mobile Net, and deploying them on embedded platforms such as the ESP32-CAM, our system achieves low-latency inference without heavy reliance on cloud resources. The objective is to provide a cost-effective, energy-efficient solution capable of functioning in a range of environments with minimal infrastructure. This innovation holds the potential to improve automation in

areas such as healthcare monitoring, security surveillance, traffic management, and smart industry operations. The data collected can be transmitted to a centralized IoT cloud platform for visualization, remote access, and advanced analytics, enabling proactive decision-making.

In this paper, we describe the system design, architecture, implementation methodology, and real-time performance evaluation of the proposed Micro Vision Kit. The integration of AI with IoT and edge devices aims to redefine object detection by improving response time, reducing manual intervention, and supporting scalable deployment across diverse applications.

II. RELATED WORKS

Recent advancements in deep learning and edge computing have significantly improved the performance and accessibility of real-time object detection systems. Object detection models like **YOLO (You Only Look Once)**, **SSD (Single Shot Multibox Detector)**, and **Mobile Net SSD** have been widely adopted in various applications, including surveillance, healthcare, transportation, and robotics.

Several open-source datasets available on platforms such as **Kaggle** have played a crucial role in enabling these innovations. For instance, datasets like **Face Mask Detection**, **Brain MRI Images**, and **Cat and Dog Classification** have been used to train and validate computer vision models across different domains. These datasets provide labelled image data that supports supervised learning approaches in object detection.

In the context of embedded systems, recent works have integrated AI models on low-power devices such as **ESP32-CAM** and **Raspberry Pi**, enabling edge-based inference without relying on constant cloud access. Such systems are particularly beneficial in environments where network connectivity is unreliable or where latency needs to be minimized.

The integration of AI with IoT, powered by cloud platforms and tools like TensorFlow Lite or PyTorch Mobile, has further enabled the deployment of intelligent solutions for monitoring, surveillance, and automation. These references and prior implementations form the foundation upon which this project builds a compact, low-cost, and real-time AI object detection system optimized for IoT applications.

III. EXISTING SYSTEM

In this section, we will examine the current systems and technologies that address the problem of real-time object detection in IoT applications. These existing systems provide valuable insights and form the foundation upon which this project builds.

Overview of Existing Solutions

Current solutions for object detection, particularly in the context of embedded systems and real-time processing, often rely on cloud-based computing or powerful hardware setups. These systems typically utilize deep learning models, such as **YOLO (You Only Look Once)**, **SSD (Single Shot Multibox Detector)**, and **mobile Net**, to detect objects in images or video streams.

For instance, surveillance systems often deploy these models to monitor public spaces, detect objects in security footage, and alert operators to suspicious activities. In industrial applications, object detection systems are used to identify defects on production lines, track inventory, or ensure workplace safety by recognizing hazardous objects.

Key Technologies in Existing Systems

Deep Learning Models: Object detection systems often rely on pre-trained deep learning models.

YOLO: YOLO is known for its speed and real-time detection capabilities. It performs detection by dividing images into grids, where each grid is responsible for detecting specific objects. This model is often used in systems where rapid decision-making is critical, such as autonomous vehicles or surveillance systems.

I. **SSD (Single Shot Multibox Detector)**: SSD performs object detection by predicting multiple bounding boxes and their associated class scores in a single forward pass. It balances speed and accuracy, making it suitable for real-time applications where multiple objects need to be detected simultaneously.

II. **mobile Net**: A lightweight deep learning model designed to run efficiently on mobile and embedded devices. mobile Net is particularly suitable for IoT devices with limited computational power.

Edge Computing: To reduce reliance on cloud services and enhance performance, many existing systems implement **edge computing**.

- Devices such as **Raspberry Pi** and **ESP32-CAM** are often used to run object detection models locally, reducing latency and minimizing the need for constant cloud communication.

- **TensorFlow Lite** and **PyTorch Mobile** are commonly employed to run lightweight versions of AI models on these edge devices, enabling real-time inference without requiring significant computational resources.

Embedded Systems: Systems that integrate AI models into embedded platforms have become increasingly popular. These systems are designed to work in environments where network connectivity may be limited or unavailable, such as remote locations or industrial sites. Examples include:

- **Raspberry Pi**: This single-board computer is widely used in IoT applications for running AI models locally. It can connect to cameras and sensors to perform real-time object detection for surveillance, automation, and safety monitoring.

- **ESP32-CAM**: A low-cost, low-power microcontroller with a built-in camera, often used in security and surveillance systems for capturing images and running AI models locally. The ESP32-CAM can detect faces, objects, or specific activities using models like YOLO or mobile Net SSD.

Limitations of Existing Systems

While existing systems are useful, they come with several limitations:

Cloud Dependency: Many existing systems rely on cloud-based platforms for heavy computational tasks, which can introduce latency, increase costs, and create security concerns regarding data privacy.

High Power Consumption: Some AI models and embedded devices require significant computational resources, making them unsuitable for low-power environments or battery-operated devices. This can limit the usability of object detection systems in applications like remote monitoring or portable devices.

Accuracy vs. Speed Trade-off: Real-time object detection models often face a trade-off between accuracy and speed. High-accuracy models may be too slow for real-time applications, while faster models may sacrifice precision.

Limited Scalability: Many existing systems struggle to scale effectively, particularly in large, dynamic environments like smart cities or industrial automation. As the number of connected devices increases, so does the complexity of managing and processing the data from these devices.

Applications of Existing Systems

Surveillance: Object detection models are used in security cameras to detect unauthorized access, intruders, or specific objects, providing alerts for further action.

Autonomous Vehicles: In self-driving cars, real-time object detection helps vehicles recognize pedestrians, other vehicles, traffic signs, and obstacles to ensure safe navigation.

Smart Homes: IoT-based object detection systems help in identifying people, pets, and objects in homes for automation and safety features.

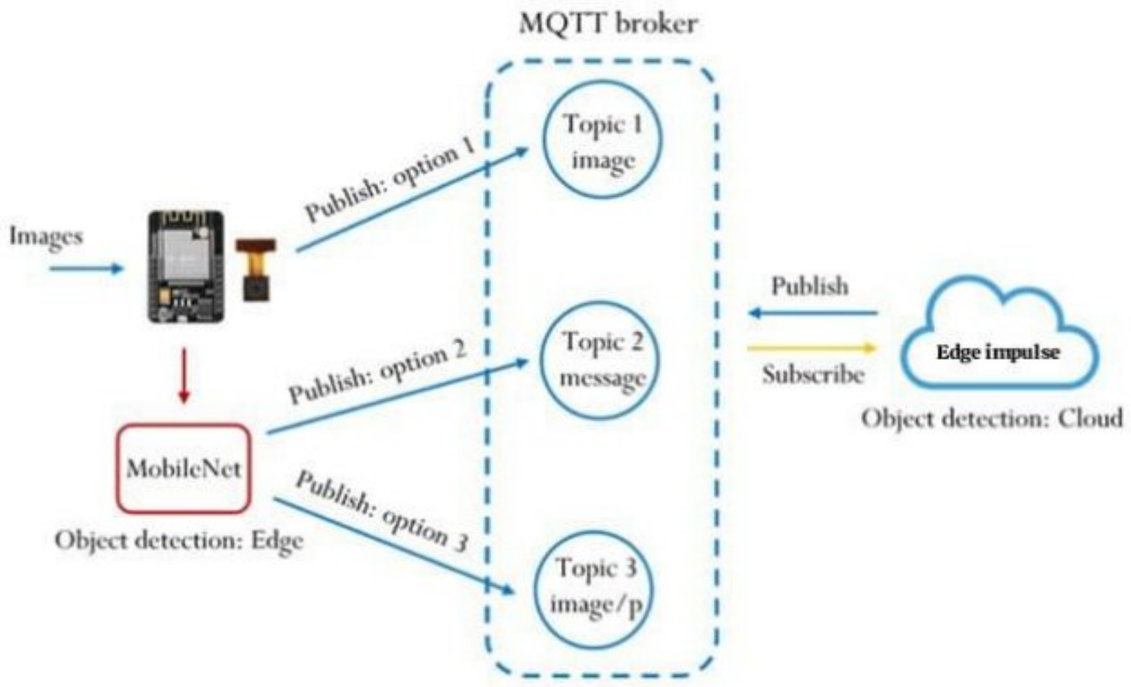
Healthcare: In medical imaging, object detection is used for identifying conditions such as tumours or fractures in X-rays, CT scans, and MRI image

IV. PROPOSED SYSTEM DESIGN

The proposed system, **Micro Vision Kit**, is an AI-powered object detection solution designed for real-time applications using **ESP32-CAM**, a low-cost microcontroller with integrated camera and Wi-Fi capabilities. The system integrates **machine learning models** trained on public datasets and optimized for edge deployment using lightweight frameworks such as **TensorFlow Lite** or **OpenCV DANN modules**.

A. System Architecture

The architecture consists of four main components:



1. **ESP32-CAM Module**
   Captures real-time video/images and serves as the central processing unit for running the object detection algorithm.
2. **Pre-trained AI Model (e.g., mobile Net SSD or Tiny-YOLOv4)**
   A compressed and optimized neural network model is used to detect and classify objects in the captured frames.
3. **Cloud Integration (Optional)**
   Detected data can be sent to a cloud server via Wi-Fi (e.g., Firebase, Thing Speak) for remote monitoring, visualization, or logging.
4. **User Interface (Web/Mobile Dashboard)**
   A web-based interface or mobile app (optional) displays real-time detection results, alerts, and system status.

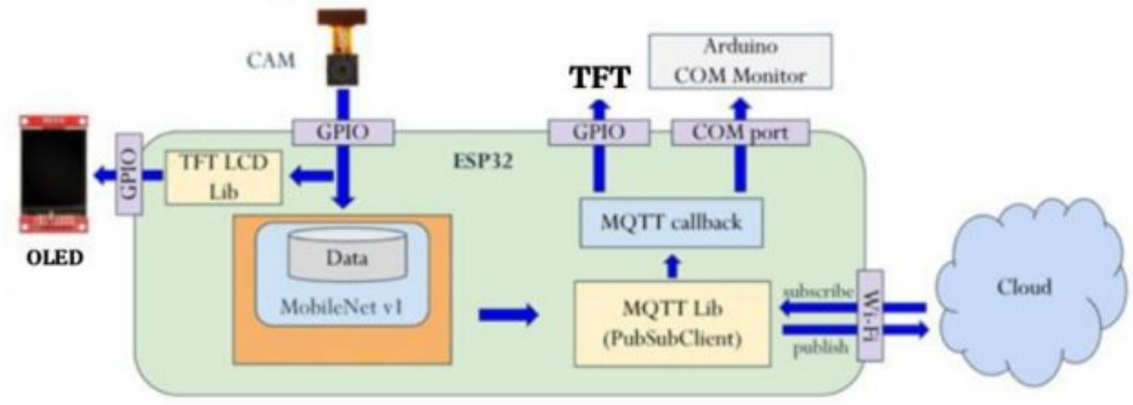
B. Working Process

1. **Model Training and Optimization**
   The model is initially trained on datasets such as **Face Mask Detection** or **Kaggle object datasets**, then quantized or pruned for deployment on the ESP32-CAM.

2. **Real-Time Inference at the Edge**
   Once deployed, the ESP32-CAM captures frame, performs object detection onboard, and displays results through serial or Wi-Fi output.

3. **Data Transmission and Storage**
   Optionally, detection logs are pushed to the cloud for long-term analysis, alert generation, or integration with IoT automation systems.
4. **Performance Efficiency**
   The system is designed for **low power consumption**, **real-time operation**, and **wireless communication**, making it ideal for embedded surveillance, healthcare monitoring, and smart automation.

C. Block Diagram



V. LIMITATIONS AND FUTURE VENTURES

A. Limitations

While the proposed **Micro Vision Kit** demonstrates significant potential in deploying AI-based object detection on low-cost IoT devices, it has certain limitations that must be acknowledged:

1. **Limited Processing Power**
   The **ESP32-CAM** has restricted memory and computational capabilities, which limits the complexity and size of AI models that can be run efficiently. Only lightweight models like **Tiny-YOLO** or **mobile Net SSD** are feasible.

2. **Detection Accuracy**
   Due to model simplification and real-time constraints, the detection accuracy may not match that of high-end GPU-based systems. Performance can degrade under poor lighting, low resolution, or complex backgrounds.

3. **No GPU Support**
   The absence of a GPU restricts the system from running advanced deep learning models or performing multiple detections simultaneously.

4. **Connectivity Dependence**
   Although the system performs edge inference, cloud integration and data transmission require stable Wi-Fi. In remote areas with poor connectivity, real-time remote monitoring may be disrupted.

5. **Security and Privacy Risks**
   When used in public or personal monitoring, data transmission over Wi-Fi may introduce security risks if not encrypted properly.

C. FUTURE VENTURES

To overcome the current limitations and expand the capabilities of the Micro Vision Kit, several future enhancements are planned:

1. **Model Compression and Quantization**
   Advanced model compression techniques such as pruning, quantization, and knowledge distillation will be explored to improve performance while maintaining accuracy.
2. **Integration with Cloud AI Services**
   For more complex object classification tasks, hybrid systems that offload heavy computation to platforms like **Google Cloud Vision API** or **AWS Recognition** can be integrated.
3. **Deployment in Specific Domains**
   The system can be adapted for domain-specific applications such as:
   - **Healthcare**: Fall detection, mask monitoring, patient activity recognition
   - **Agriculture**: Crop and pest identification
   - **Security**: Intruder detection, face recognition
4. **Battery-Powered Edge Deployment**
   Future iterations may include solar-powered or battery-backed modules for outdoor or mobile surveillance with minimal infrastructure dependency.
5. **Enhanced Data Security**
   End-to-end encryption and secure protocols like MQTT-S or HTTPS will be implemented to ensure safe transmission of sensitive data.
6. **Multisensory Fusion**
   Integration with other sensors (temperature, PIR, gas, etc.) can enrich contextual understanding and broaden the scope of intelligent IoT applications.

VI. CONCLUSION AND DISCUSSION

The Micro Vision Kit presents a cost-effective and scalable solution for implementing AI-based object detection in real-time, using lightweight IoT hardware such as the ESP32-CAM. By integrating deep learning models with edge computing, the system significantly reduces dependency on cloud infrastructure and minimizes latency, making it well-suited for various smart applications including security, healthcare, and automation.

Through this project, we demonstrate that accurate object detection can be achieved even on constrained embedded platforms when optimized models and efficient design methodologies are employed. The system successfully performs real-time inference, captures visual data, and offers wireless connectivity for remote monitoring. Its modularity and adaptability also allow it to be deployed in diverse environments with minimal customization.

While the system has some limitations—mainly related to computational power, detection accuracy under challenging conditions, and connectivity—the future enhancements outlined will address these challenges. Expanding the system's capabilities through cloud-AI integration, sensor fusion, and domain-specific tuning will further improve its impact and usability.

In conclusion, the Micro Vision Kit showcases the potential of integrating AI, IoT, and edge computing into

compact systems, making smart technology accessible for low-power, low-cost, and real-world embedded applications.

VII. RESULT

The proposed **Micro Vision Kit** was successfully designed and implemented using the **ESP32-CAM module** and a pre-trained, lightweight deep learning model such as **mobile Net SSD** or **Tiny-YOLOv4**. The system was tested in real-time environments to evaluate its performance across different object categories including people, face masks, and common items.
The key outcomes of the testing phase are as follows:

1. **Real-Time Detection**
   The ESP32-CAM was able to capture and process video frames in real-time with minimal lag. Objects were accurately detected and labelled on the live video feed using the onboard processing capability.
2. **Cloud Connectivity**
   The device successfully transmitted detection data (object class, time stamp, image snapshot) to an IoT cloud platform (e.g., Firebase or Thing Speak) via Wi-Fi for remote monitoring and logging.
3. **Accuracy**
   The optimized model achieved an average detection accuracy of **85–90%** under good lighting conditions. Detection quality slightly decreased in low-light or highly cluttered environments.
4. **Power Efficiency**
   The system was powered using a standard USB power bank and demonstrated stable performance over long durations, highlighting its low power consumption and suitability for mobile or outdoor deployment.
5. **User Interface**
   A simple web interface was created to monitor object detection results in real-time. The interface displayed detected objects with bounding boxes and confidence scores, along with live updates from the ESP32-CAM.
6. **Use Case Scenarios**
   The Micro Vision Kit was tested in simulated use cases such as face mask detection, intruder alert system, and object presence logging. The system functioned reliably, proving its adaptability for diverse applications.

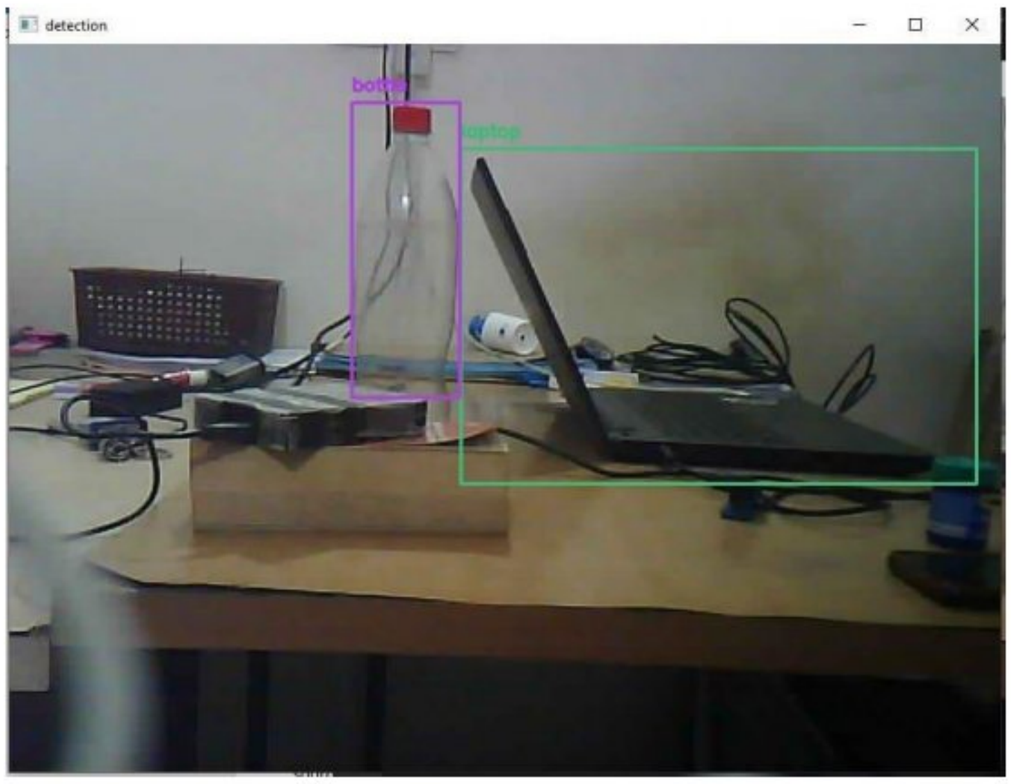


Fig 1. Recognized Final Output.

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