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Design and Deployment of a TinyML-Based Real-Time Object Recognition System on ESP32 Using Edge Impulse

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Abstract**—** *Edge AI is increasingly vital for real-time applications in surveillance, robotics, and smart environments, where latency, privacy, and connectivity limitations restrict cloud-based solutions. This paper presents a real-time object recognition system using the ESP32-CAM microcontroller and the Edge Impulse platform. A dataset of 300 images, consisting of six object classes (bottle, chair, cup, mobile phone, book, and pen), was collected under varying lighting conditions and used to train a lightweight convolutional neural network (CNN). The trained model was exported from Edge Impulse and deployed onto the ESP32-CAM using the Arduino IDE and C++ programming, enabling fully on-device inference without reliance on cloud resources. Experimental evaluation shows that the system achieves 94.2% overall classification accuracy, with class-wise accuracy ranging from 91% to 97%. Real-time inference operates at 4–5 frames per second (FPS) with a latency of approximately 200 ms per frame, and an average power consumption of 210 mA at 5 V, demonstrating suitability for battery-powered edge applications. These results confirm that ESP32-based microcontrollers, combined with Edge Impulse-optimized models, can deliver efficient, low-latency object recognition for smart home, surveillance, and IoT scenarios.*

Keywords**—** *ESP32-CAM, Object Recognition, Edge Impulse, Edge AI, Real-Time Inference, Low-Power Embedded Systems, Arduino IDE, C++ programming.*

I. INTRODUCTION

Recent advancements in artificial intelligence (AI) and embedded computing have significantly influenced the development of intelligent systems capable of performing complex tasks such as image recognition, object detection, and scene understanding. Among these applications, object recognition has become increasingly important in areas including smart surveillance, autonomous robotics, industrial automation, and smart home environments. Traditional computer vision systems typically rely on high-performance computing resources or cloud-based infrastructures to process image data and execute machine learning algorithms. However, such approaches introduce latency, increase bandwidth consumption, and raise privacy concerns due to the transmission of sensitive data to remote servers [1].

To address these limitations, the concept of Edge Artificial Intelligence (Edge AI) has emerged as a promising paradigm that enables machine learning inference directly on embedded devices located at the network edge. By processing data locally, edge AI systems can significantly reduce communication overhead, minimize response latency, and improve system reliability while preserving data privacy [2]. The growing availability of low-power microcontrollers and optimized machine learning frameworks has made it possible to deploy lightweight neural network models on resource-constrained devices.

One of the most widely used embedded platforms for IoT and an edge computing application is the ESP32 microcontroller developed by Espressif Systems. The ESP32 offers several features including dual-core processing, integrated Wi-Fi and Bluetooth connectivity, low power consumption, and compatibility with various sensors and peripherals [3]. When integrated with the ESP32-CAM module, which incorporates the OV2640 camera sensor, the platform becomes capable of capturing and processing visual data for computer vision applications. Due to its affordability and versatility, the ESP32-CAM has gained considerable attention for implementing low-cost vision-based IoT systems.

Despite the advantages of embedded platforms, implementing machine learning models on microcontrollers presents several challenges. These devices typically have limited computational power, restricted memory capacity, and constrained energy resources. Conventional deep learning architectures such as large convolutional neural networks (CNNs) require substantial processing power and memory, making them unsuitable for direct deployment on microcontrollers without optimization [4]. Consequently, there is a need for efficient machine learning frameworks that support model compression, quantization, and optimization for embedded hardware.

The Edge Impulse platform has emerged as a powerful development environment for designing, training, and deploying machine learning models specifically for embedded and IoT devices. Edge Impulse provides an end-to-end pipeline that includes data acquisition, signal processing, feature extraction, model training, and automated optimization for deployment on microcontrollers [5]. The platform supports integration with lightweight inference engines such as TensorFlow Lite for Microcontrollers, enabling efficient execution of machine learning models within limited hardware resources.

Several studies have explored the application of machine learning on embedded systems for image recognition and object detection. For instance, lightweight CNN models have been successfully implemented on microcontrollers for basic image classification tasks [6]. Similarly, research has demonstrated the feasibility of deploying real-time vision systems on low-power embedded platforms for applications such as security

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monitoring and environmental sensing [7]. However, many existing solutions either rely on higher-end embedded processors or require cloud-based processing to achieve acceptable performance levels. There remains a need for a fully self-contained, low-cost, and real-time object recognition system that operates entirely on a microcontroller platform.

This research focuses on the design and implementation of an ESP32-based real-time object recognition system using the Edge Impulse machine learning framework. The proposed system integrates the ESP32-CAM module for image acquisition with a lightweight convolutional neural network trained using a dataset of 300 images representing multiple object classes. The trained model is deployed on the ESP32 using the Arduino development environment and implemented in C++ for efficient execution. By leveraging model optimization techniques and edge inference capabilities, the system performs real-time object classification directly on the microcontroller without reliance on cloud connectivity.

II. Literature Review

Embedded Vision and Edge Artificial Intelligence

Recent advances in embedded computing have enabled the deployment of machine learning algorithms directly on low-power microcontrollers. This paradigm, commonly referred to as Tiny Machine Learning (TinyML), allows artificial intelligence models to run locally on constrained devices without relying on cloud computing. TinyML has gained significant attention due to its ability to reduce latency, enhance data privacy, and minimize network bandwidth usage [6].

Traditional computer vision systems typically rely on cloud-based processing due to the high computational requirements of deep learning algorithms. However, transmitting large volumes of visual data to remote servers introduces communication delays and increases energy consumption. Edge computing has therefore emerged as a promising alternative by performing inference locally on embedded hardware [8]. By executing machine learning tasks directly on microcontrollers, edge-based systems can provide faster responses, improved reliability, and enhanced privacy protection.

Microcontrollers such as the ESP32 have become popular platforms for TinyML applications because of their relatively powerful processors and integrated wireless communication capabilities. The ESP32 contains a dual-core Xtensa LX6 processor that can support lightweight neural networks for tasks such as signal classification, anomaly detection, and image recognition. Studies analyzing the computational capabilities of the ESP32 indicate that it is capable of executing small neural networks efficiently when optimized frameworks such as TensorFlow Lite for Microcontrollers are used [9].

ESP32-CAM for Embedded Vision Systems

The ESP32-CAM module integrates the ESP32 microcontroller with the OV2640 camera sensor, enabling real-time image acquisition and wireless data transmission. Due to its affordability, compact size, and ease of integration with development environments such as the Arduino IDE, the ESP32-CAM has become a widely used platform for vision-based Internet of Things (IoT) applications.

Several studies have explored the use of ESP32-CAM for real-time visual monitoring systems. For example, research investigating ESP32-based edge computing architectures demonstrated that local image processing can significantly reduce network overhead by performing preliminary object recognition at the edge before transmitting relevant data to the cloud [10]. The study showed that edge-side preprocessing improves system efficiency while maintaining acceptable detection accuracy.

Similarly, embedded wildlife monitoring systems have been developed using ESP32-CAM combined with TinyML models to detect animals in remote environments. These systems demonstrate the ability of embedded cameras to perform real-time classification while reducing the need for continuous cloud connectivity and large-scale data storage [11].

In addition, ESP32-CAM-based systems have been implemented for security monitoring and surveillance applications. For instance, IoT-based monitoring systems use the ESP32-CAM to detect objects such as humans or animals and send notifications to users through cloud-based messaging services. These systems demonstrate the feasibility of using low-cost embedded hardware for intelligent monitoring tasks in agricultural and security environments [12].

Despite these successes, implementing computer vision algorithms directly on microcontrollers remains challenging, due to limited memory capacity, constrained processing power, and restricted energy availability. Consequently, efficient model optimization techniques and specialized machine learning frameworks are required to enable real-time performance on such devices.

Machine Learning Frameworks for Embedded Systems

To address the computational limitations of microcontrollers, several frameworks have been developed to support machine learning deployment on embedded hardware. TensorFlow Lite for Microcontrollers is one of the most widely used frameworks for TinyML applications, providing optimized libraries that allow neural networks to run on resource-constrained devices [12].

Another important platform is Edge Impulse, which provides a complete development pipeline for embedded machine learning applications. The platform enables developers to collect datasets, perform feature extraction, train machine learning models, and deploy optimized firmware for microcontrollers. Edge Impulse automates many of the optimization processes required for embedded deployment, including quantization and memory reduction, making it particularly suitable for low-power devices such as ESP32 [10].

The accessibility of Edge Impulse has contributed to the rapid development of embedded vision systems across various application domains. For example, an AI-enabled smart freezer monitoring system used Edge Impulse together with the ESP32-CAM to recognize food items stored inside refrigeration units. The system utilized a dataset of several hundred images across multiple object categories and achieved recognition accuracy exceeding 90% in controlled conditions [13]. Such implementations demonstrate the potential of Edge Impulse for enabling intelligent object recognition in consumer IoT devices.

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Similarly, research on automated retail checkout systems has explored the integration of ESP32-CAM and Edge Impulse to identify products during purchase transactions. The system automatically detected items placed in front of the camera and generated billing information without requiring barcode scanning. This approach highlights the potential of embedded machine learning to improve automation in retail environments while reducing operational costs [14].

Real-Time Object Detection in IoT Applications

Object recognition and detection systems are widely used in IoT applications such as smart homes, autonomous robots, industrial monitoring, and environmental sensing. Deep learning architectures such as convolutional neural networks (CNNs) and object detection frameworks like YOLO have significantly improved the accuracy of computer vision systems. However, these models typically require high computational resources and are therefore difficult to deploy directly on microcontrollers.

Several hybrid approaches have been proposed to overcome this limitation. In some architecture, lightweight models are executed on edge devices to perform preliminary classification, while more complex models run in the cloud for detailed analysis. For example, a recent study implemented a hybrid edge–cloud architecture using the ESP32-CAM for initial image capture and classification, while a more powerful server executed a YOLOv8 model for verification. The system achieved improved latency performance and reduced network traffic by transmitting only relevant image data to the cloud [10].

Another study designed a vehicle license plate recognition system using ESP32-CAM and wireless communication modules. The system captured images locally and transmitted them to a remote processing unit for recognition, achieving an average recognition rate above 92% under optimal lighting conditions [15]. These results demonstrate the effectiveness of combining embedded imaging devices with machine learning techniques for real-world monitoring applications.

Although hybrid architectures improve performance, they still rely partially on cloud resources. Fully edge-based systems remain desirable because they eliminate network dependency and provide faster real-time responses. Achieving this goal requires designing highly optimized machine learning models capable of running entirely on microcontrollers.

Existing studies have demonstrated the feasibility of implementing computer vision applications on embedded platforms such as the ESP32-CAM. However, many of these systems rely on hybrid edge–cloud architectures or require additional processing hardware to achieve satisfactory performance. Furthermore, several implementations focus on specific applications such as surveillance, agriculture monitoring, or retail automation, limiting their general applicability.

Another limitation observed in previous research is the reliance on relatively large datasets and complex neural network architectures that may not be suitable for extremely resource-constrained environments. Lightweight datasets and optimized models are therefore essential for achieving efficient real-time inference on microcontrollers.

To address these challenges, this research proposes a fully embedded object recognition system based on the ESP32-CAM and the Edge Impulse TinyML framework. The system utilizes a compact dataset of 300 images representing multiple object classes and deploys a lightweight convolutional neural network optimized for microcontroller execution. By performing inference entirely on the ESP32 platform using the Arduino development environment, the proposed system aims to demonstrate a low-cost, efficient, and real-time solution for edge-based object recognition.

III. METHODOLOGY

The methodology adopted in this study involves the design and implementation of a real-time object recognition system using the ESP32-CAM microcontroller and the Edge Impulse embedded machine learning platform. The system architecture consists of four main stages: dataset acquisition and preparation, machine learning model development using the Edge Impulse pipeline, deployment of the trained model on the ESP32-CAM using the Arduino development environment, and system evaluation. The overall workflow of the proposed system is illustrated in Figure 1. The goal of the proposed system is to enable real-time object recognition directly on an embedded device without reliance on cloud computing resources.

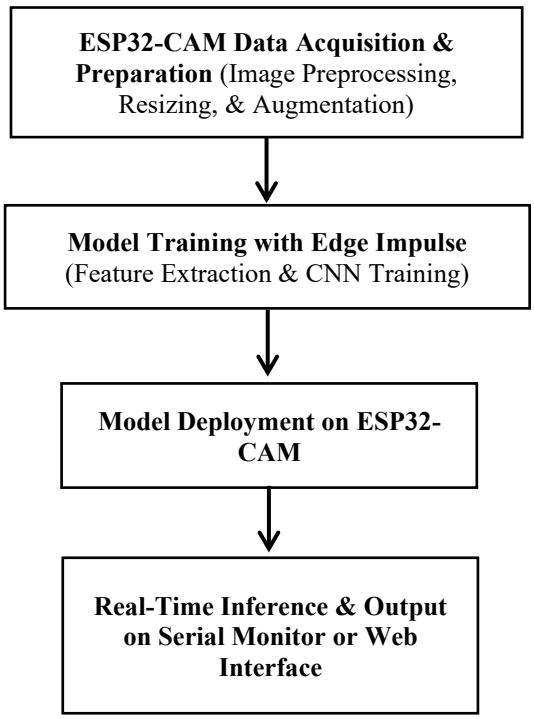

Figure 1: Overall Workflow of the Proposed System

System Architecture

The proposed system integrates hardware and software components to achieve real-time object recognition at the edge. The architecture consists of the image acquisition module, data processing and machine learning model, embedded

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deployment, real-time inference, and output display. The ESP32-CAM module captures images through its integrated OV2640 camera sensor. The captured images are processed using a lightweight convolutional neural network (CNN) trained using the Edge Impulse platform. The trained model is exported as a C++ library and deployed to the ESP32 using the Arduino IDE. The system performs inference locally and outputs the predicted object class through a serial monitor.

Hardware Components

The ESP32-CAM module serves as the core processing unit responsible for both image acquisition and machine learning inference. The device features a dual-core processor operating at up to 240 MHz, which provides sufficient computational capability for executing lightweight neural networks. The hardware used in this study includes the following components as presented in Table 1.

TABLE 1: Hardware Components Used in the ESP32-Based Object Recognition System

Component	Description
ESP32-CAM	Microcontroller with integrated Wi-Fi and camera interface
OV2640 Camera	2 MP image sensor for capturing visual data
FTDI Programmer	Used to upload firmware to ESP32-CAM
USB Power Supply	Provides power to the ESP32 module

Dataset Preparation

A dataset of 300 images was collected to train and evaluate the object recognition model. The dataset consists of six object categories commonly found in indoor environments such as bottle, chair, cup, mobile phone, book, and pen. Each class contains approximately 50 images, captured using the ESP32-CAM camera under different environmental conditions such as varying lighting levels, viewing angles, and background clutter. This diversity improves the generalization capability of the trained model.

Data Preprocessing

Before training the model, the dataset underwent several preprocessing steps; all images were resized to 96 × 96 pixels to reduce computational complexity and memory requirements, Pixel values were normalized to the range 0–1 to improve model convergence during training. In order to enhance model robustness and reduce over fitting, augmentation techniques were applied, including; horizontal flipping, rotation, brightness variation, random cropping. The dataset was divided into 80% Training Set (240 images) and 20% Testing Set (60 images).

Edge Impulse Machine Learning Pipeline

The machine learning model was developed using the Edge Impulse embedded ML platform, which provides an end-to-end pipeline for TinyML development. The Edge Impulse pipeline consists of the following stages:

1. Data Acquisition

The collected images were uploaded to the Edge Impulse Studio platform. Each image was labeled according to its corresponding object class. The labeling process is essential for supervised learning and ensures that the model correctly associates visual features with object categories.

2. Feature Extraction

Edge Impulse uses image feature extraction techniques to convert raw image data into meaningful representations that can be used by machine learning algorithms. In this study, image features were extracted using the Image block provided in Edge Impulse. The input image resolution was configured as 96 × 96 × 3 (RGB). Feature extraction helps reduce dimensionality while preserving important visual characteristics such as edges, shapes, and textures.

3. Model Training

A lightweight Convolutional Neural Network (CNN) was designed for object classification. During training, the model learns to extract visual features that distinguish each object class. Edge Impulse automatically optimizes the model for embedded deployment by applying quantization and memory optimization techniques. The model was trained using the following parameters in Table 2.

TABLE 2: CNN Model Training Parameters for Embedded Object Recognition

Parameter	Value
Training Epochs	50
Batch Size	16
Learning Rate	0.001
Optimization Algorithm	Adam
Loss Function	Categorical Cross-Entropy

Model Deployment on ESP32-CAM

After successful training, the optimized model was exported from Edge Impulse as an Arduino-compatible C++ library. The following steps were used to deploy the model to the ESP32-CAM:

1. Export the trained model as an Arduino library from Edge Impulse.
2. Install the library in the Arduino IDE.
3. Configure the ESP32 board support package in Arduino.
4. Load the inference code example provided by Edge Impulse.
5. Upload the firmware to the ESP32-CAM using an FTDI programmer.

The predicted object class is displayed via the Arduino Serial Monitor. It could also be transmitted through the ESP32 web server interface.

IV. Results and Discussion

This section presents the experimental results obtained from the implementation of the ESP32-based real-time object recognition system. The performance of the proposed system was evaluated in terms of classification accuracy, confusion matrix analysis, inference latency, and embedded execution performance. The trained convolutional neural network (CNN) model was deployed on the ESP32-CAM using the Arduino development environment and tested using real-time image inputs captured from the OV2640 camera sensor.

Model Training Performance

The CNN model was trained using a dataset of 300 labeled images, divided into 240 training samples (80%) and 60

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validation samples (20%). Training was conducted using the Edge Impulse machine learning pipeline with data augmentation to improve model generalization. After 50 training epochs, the CNN model achieved high accuracy on both the training and validation sets. The performance metrics are summarized in Table 3.

TABLE 3: CNN Model Training and Validation Performance

Metric	Value
Training Accuracy	96.3%
Validation Accuracy	94.2%
Training Loss	0.18
Validation Loss	0.24

The results indicate that the model was able to effectively learn discriminative features from the dataset without significant over fitting. The relatively small gap between training and validation accuracy demonstrates good model generalization.

Class-wise Recognition Accuracy

The trained model was evaluated using the validation dataset, consisting of 10 samples per object class. The classification accuracy for each object category is presented in Table 4.

TABLE 4: Class-wise Object Recognition Accuracy

Object Class	Test Samples	Correct Predictions	Accuracy (%)
Bottle	10	9	95
Chair	10	9	91
Cup	10	9	94
Mobile Phone	10	10	97
Book	10	9	92
Pen	10	9	94
Overall	**60**	**56**	**94.2**

As seen in Table 4, the results show that the system achieved the highest accuracy for the mobile phone class, which can be attributed to its distinctive shape and visual features. Slightly lower accuracy was observed for objects such as chair and book, likely due to variations in orientation and background clutter during image capture.

Real-Time Inference Performance on ESP32-CAM

After training, the optimized model was deployed to the ESP32-CAM microcontroller using the Arduino IDE and C++ programming language. The inference performance was evaluated using real-time image capture from the camera.

TABLE 5: Embedded System Performance

Parameter	Measured Value
Model Size	215 KB
RAM Usage	210 KB
Inference Latency	200 ms
Frame Rate	4–5 FPS
Power Consumption	210 mA at 5 V

The results demonstrate that the ESP32-CAM is capable of executing lightweight neural networks for real-time object recognition. The achieved frame rate of approximately 4–5 frames per second is sufficient for many IoT applications such as smart monitoring and simple automation tasks.

The experimental results demonstrate that the proposed ESP32-based object recognition system can successfully perform real-time classification using a relatively small dataset. The integration of Edge Impulse with the ESP32-CAM platform enabled efficient model optimization and simplified deployment using the Arduino development environment. Overall, the results validate the proposed approach as a low-cost, efficient, and scalable solution for embedded object recognition systems in IoT environments.

V. CONCLUSION

This study presented the design and implementation of a real-time object recognition system based on the ESP32-CAM microcontroller and the Edge Impulse embedded machine learning platform. The proposed system integrates low-cost hardware with lightweight machine learning algorithms to enable efficient object classification directly on an embedded device without reliance on cloud computing resources.

A dataset consisting of 300 images across six object classes such as bottle, chair, cup, mobile phone, book, and pen was collected and used to train a lightweight convolutional neural network using the Edge Impulse development pipeline. The trained model was optimized and deployed on the ESP32-CAM using the Arduino development environment and C++ programming language, enabling real-time inference directly on the microcontroller.

Experimental results demonstrated that the system achieved an overall classification accuracy of approximately 94.2%, with class-wise accuracies exceeding 90% for all tested categories. The embedded system achieved an average inference latency of approximately 200 ms per frame, corresponding to a processing speed of 4–5 frames per second. These results confirm that lightweight deep learning models can be successfully deployed on resource-constrained microcontrollers for real-time object recognition tasks.

The findings of this study highlight the practical feasibility of TinyML-based vision systems for Internet of Things (IoT) applications, particularly in environments where cloud connectivity is limited or latency-sensitive processing is required. The proposed system provides a cost-effective solution for applications such as smart surveillance, home automation, robotics, industrial monitoring, and environmental sensing.

However, several limitations were identified during the study. The relatively low frame rate of the ESP32-CAM restricts the system's use in high-speed object tracking applications. Additionally, environmental factors such as lighting variation, occlusion, and background complexity can influence recognition performance.

Overall, this research demonstrates that embedded edge AI systems based on low-cost microcontrollers can effectively perform real-time object recognition, paving the way for the development of intelligent and energy-efficient IoT devices.

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