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Development and evaluation of a TinyML-based sensor fusion system for medical waste classification on low-cost embedded devices

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ABSTRACT

Background: Medical waste management in resource-limited healthcare facilities remains dominated by manual segregation, which is error-prone and difficult to standardize. Existing automated solutions often rely on cloud-based deep learning or high-cost hardware, limiting real-time deployment at the point of waste generation.

Objective: This study aimed to develop and evaluate a medical waste classification system integrating Tiny Machine Learning (TinyML) and multi-sensor fusion on a low-cost embedded device to achieve accurate, real-time, and resource-efficient on-device inference.

Method: An experimental system design approach was employed, including dataset construction, model development, and embedded deployment. A TinyML-optimized MobileNetV2 model was integrated with heterogeneous sensor fusion and evaluated under embedded constraints to assess classification performance, latency, and memory usage.

Result: The vision-only model achieved an accuracy of 84.5%, with frequent misclassification of sharps waste. After integrating sensor fusion, overall accuracy increased to 96.5%, and recall for sharps reached 98%. The system demonstrated efficient on-device inference with an average latency of 280 ms and low memory consumption (<1 MB).

Conclusion: The proposed TinyML-based sensor fusion system provides a robust, accurate, and cost-effective solution for automated medical waste classification. This approach enhances healthcare worker safety and supports scalable deployment in resource-limited healthcare environments.

INTRODUCTION

Medical waste management remains a major global public health and environmental challenge due to the increasing generation of hazardous healthcare waste. According to the World Health Organization (WHO), approximately 15% of healthcare waste is hazardous, and nearly one-third of healthcare facilities worldwide do not adequately manage it, particularly in low- and middle-income countries. Inadequate waste handling increases the risk of disease transmission, needlestick injuries, and environmental contamination, posing significant risks to healthcare workers, patients, and surrounding communities.[1,2]

Recent studies have explored vision-based systems for waste classification to improve real-time segregation at the point of generation. However, existing artificial intelligence (AI) solutions generally fall into two categories with inherent limitations. Cloud- or GPU-based deep learning systems achieve high accuracy but require substantial computational resources and stable internet connectivity, limiting their applicability in decentralized settings. In contrast, vision-only embedded systems improve hardware efficiency but rely solely on visual input, making them highly sensitive to lighting conditions, occlusion, and background noise, which reduces performance stability in real-world environments.[3]

Current approaches tend to optimize either computational performance in high-resource environments or hardware efficiency in vision-only systems, without adequately addressing perceptual ambiguity and multimodal robustness. Consequently, there remains a critical need for lightweight and reliable classification systems capable of operating autonomously on low-cost embedded devices while overcoming the limitations of visual inference alone.[4-6]

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To address this gap, this study develops a TinyML-based medical waste classification system implemented on a low-cost embedded platform, integrating a MobileNetV2-based model with heterogeneous sensor fusion. By combining visual inference with non-visual sensor inputs, the proposed system improves classification stability under real-world conditions while maintaining low latency and minimal memory usage. This approach provides a resource-efficient alternative to cloud-dependent and vision-only AI systems.[7]

Furthermore, unlike previous studies that primarily focus on visual recognition accuracy, this study incorporates complementary physical sensing modalities to reduce perceptual ambiguity. The integration of a TinyML-optimized MobileNetV2 model with inductive and weight-based sensors enables fully on-device inference that balances accuracy, computational efficiency, and robustness. This edge-centric multimodal architecture represents a distinct methodological contribution beyond conventional vision-based or cloud-dependent systems.

METHOD

Study Design

This study employed an experimental system design approach based on Tiny Machine Learning (TinyML) to develop and systematically evaluate a medical waste classification system deployed on a low-cost embedded device. The system was designed to operate under embedded constraints, emphasizing computational efficiency, robustness, and real-time on-device inference without reliance on cloud-based processing.

System Architecture

The system was designed to classify medical waste into four predefined categories: sharps, pathological waste, infectious waste, and linen. The classification pipeline consisted of five stages: (1) real-time image acquisition using an embedded camera, (2) image preprocessing and TinyML-based visual inference, (3) acquisition of complementary non-visual sensor data, (4) sensor fusion to refine classification decisions, and (5) generation of the final output class. All processes were executed locally on the embedded device to enable autonomous operation.[8]

Dataset Construction

The dataset comprised 800 labeled images representing four medical waste categories (200 images per class). Images were collected from healthcare environments and supplemented with publicly available datasets to increase variability. Image acquisition was performed using both a smartphone camera and an OV2640 embedded camera module to ensure consistency between training and deployment conditions.[9] To simulate real-world conditions, two acquisition scenarios were included: single-object images and multi-object images containing up to three waste items.[10]

Data Splitting and Augmentation

The dataset was split into training and test sets at 80:20 (640 training images and 160 test images). Data augmentation, including rotation, scaling, and brightness adjustment, was applied exclusively to the training set to improve generalization under variable conditions.[11]

Model Development

A MobileNetV2-based convolutional neural network (CNN) was used due to its lightweight architecture and suitability for embedded deployment. Transfer learning was applied by fine-tuning the final classification layers on the four-class dataset. Input images were resized to 96 × 96 pixels in RGB. The model was trained using categorical cross-entropy loss and the Adam optimizer with a learning rate of 1×10^{-3} for 50 epochs.

Model Optimization

To enable efficient embedded deployment, the trained model was quantized to an 8-bit integer (int8) format and converted to TensorFlow Lite for Microcontrollers (TFLite Micro). This optimization reduced memory usage and computational complexity while maintaining classification performance. The final model contained approximately 0.21 million parameters, making it suitable for low-memory environments.[12,13]

Embedded Implementation and Evaluation

The optimized model was deployed on an ESP32-CAM platform with an OV2640 camera module. All inference processes were executed locally on the device. Performance was evaluated using classification metrics (accuracy, precision, recall, and F1-score) and embedded performance indicators, including inference latency and memory usage. Latency was measured as the time between image capture and output generation, averaged over 100 inference cycles. Memory usage was assessed based on compiled model size and runtime allocation. The evaluation was designed to assess both classification performance and the feasibility of the embedded system under real-time operating conditions.[14-17]

Ethical Approval

This study was approved by the Health Research Ethics Committee of Universitas Aisyiyah Yogyakarta (Approval No. 4964/KEP UNISA/XII/2025).

RESULTS

System Development Output

The developed system resulted in a functional embedded device that integrates a TinyML-based classification model with sensor-fusion capabilities. The system was implemented on an ESP32-CAM platform equipped with an OV2640 camera, an inductive sensor, and a load cell, enabling real-time classification of medical waste. The physical implementation of the system is presented in Figure 1.

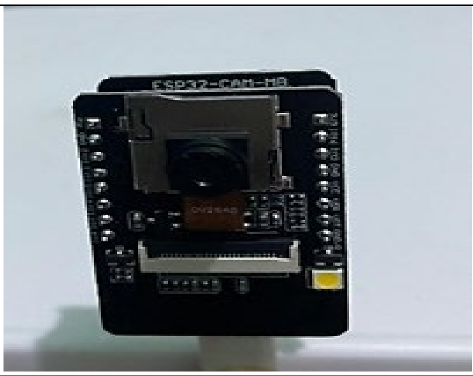

Figure 1. Developed a TinyML-based Embedded Device for Real-time Medical Waste Classification

Figure 2. Real-time On-device Classification Output Showing Predicted Medical Waste Category and Confidence Score Using the TinyML-based Sensor Fusion System

Performance of the Vision-Only Model

The quantized MobileNetV2 (int8) model was initially evaluated using vision-only inference on the ESP32-CAM platform. Testing was conducted on 160 images evenly-distributed across four classes: sharps, pathological, infectious, and linen. The vision-only model achieved an overall classification accuracy of 84.5%. Confusion matrix analysis revealed notable misclassification in the sharps category, with approximately 12% of samples incorrectly classified as Infectious waste. These errors were primarily associated with small object size, partial occlusion, and variations in lighting conditions.

Performance with Sensor Fusion

After integrating the heterogeneous sensor fusion module, classification performance improved substantially. The combined use of visual inference and non-visual sensor inputs (inductive and load-cell sensors) enhanced discrimination among visually similar waste categories. Overall classification accuracy increased to 96.5%, an absolute improvement of 12.0 percentage points over the vision-only model. Recall for sharps improved from 82% to 98%, primarily due to the inductive sensor's ability to detect metallic objects. The load cell sensor improved classification of Pathological and Linen waste by providing mass-based validation, particularly under conditions where visual features were ambiguous.

Class-Wise Performance Comparison

Sensor fusion consistently improved performance across all classes, with the largest gain observed in the sharps category (+16.0%) (Table 1).

Table 1. Performance Comparison between Vision-only and Sensor Fusion Models Across Medical Waste Categories

Waste Type	Accuracy (Vision Only)	Accuracy (Sensor Fusion)	Improvement
Sharps	82.0%	98.0%	+16.0%
Pathological	85.0%	95.0%	+10.0%
Infectious	83.0%	94.0%	+11.0%
Linen	88.0%	99.0%	+11.0%
Average	84.5%	96.5%	+12.0%

Embedded System Performance

The system demonstrated efficient on-device inference, with an average latency of approximately 280 ms and low memory consumption (<1 MB). These results confirm the feasibility of deploying the proposed model on low-cost embedded hardware for real-time medical waste classification (Figure 2).

DISCUSSION

The findings of this study demonstrate that improved classification performance is primarily driven by heterogeneous sensor fusion. The vision-only TinyML model achieved 84.5% accuracy but showed notable limitations in classifying small or partially occluded sharp objects. After integrating sensor fusion, overall accuracy increased to 96.5%, with a substantial improvement in sharp classification (recall increased from 82% to 98%).

These improvements can be explained by the complementary nature of the sensing modalities. Vision-based models rely on visual features, which are sensitive to lighting variation, occlusion, and limited image resolution in embedded environments. The addition of an inductive proximity sensor enabled the detection of metallic properties, allowing the system to correctly identify visually ambiguous sharp objects. In parallel, the load cell sensor provided mass-based contextual information, improving discrimination between visually similar categories such as pathological waste and contaminated linen.

The hierarchical fusion of visual and non-visual data reduced reliance on a single modality and enhanced classification robustness under real-world conditions. This multimodal integration is particularly important in embedded healthcare settings, where environmental variability may compromise the reliability of vision-only systems.[18-21]

Previous studies in medical waste classification have primarily focused on improving visual recognition performance through more complex deep learning models. In contrast, the present study introduces a different approach by integrating multimodal sensing rather than increasing model complexity. This approach represents a shift from vision-centric optimization toward a more application-oriented strategy that incorporates physical characteristics relevant to medical waste classification.[22]

By integrating sensor-derived features such as metal presence and mass, the proposed system addresses inherent limitations of visual perception, particularly in scenarios involving occlusion or visually similar objects. This approach not only improves classification accuracy but also aligns more closely with the physical risk characteristics of medical waste, such as the identification of sharps materials.[23,24]

This study has several limitations. The dataset was relatively small and may not fully reflect the diversity of medical waste encountered across different healthcare settings. In addition, the evaluation was conducted under controlled conditions, which may not capture all real-world variability. Despite these limitations, the proposed system demonstrates strong potential for practical implementation in resource-limited healthcare environments. Future studies should include larger datasets, multi-center validation, and integration with automated waste management systems to further enhance scalability and applicability.

CONCLUSIONS AND RECOMMENDATION

This study demonstrates that a TinyML-based medical waste classification system implemented on a low-cost embedded platform (ESP32-CAM) is technically feasible and enables resource-efficient real-time waste categorization. The integration of a MobileNetV2 TinyML model with heterogeneous sensor fusion significantly improves classification robustness and reduces errors in vision-only inference, particularly for safety-critical waste categories. By combining visual and non-visual sensing modalities within an on-device architecture, the proposed system enhances decision stability under embedded constraints without reliance on cloud or high-performance computing infrastructure. Future research should evaluate the system's generalizability across diverse healthcare settings, expand the classification categories, and investigate adaptive learning mechanisms to accommodate environmental variability. Integration with broader healthcare monitoring systems may further support scalable deployment and long-term validation.

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