ADBA Computers and Electronics in Medicine
Cutting-Edge Scientific Solutions

**e-ISSN: 3023-8609**
**RESEARCH ARTICLE**
**Vol.**3 / **No.**1 / 2026 / **pp.**86-93
https://doi.org/10.69882/adba.cem.20260110

# TinyML-Based Machine Learning System for Multi-Class Ear Condition Classification

**Serkan Dişlitaş** [*,1]
[*]Hitit University, Faculty of Engineering and Natural Sciences, Department of Computer Engineering, 19030, Çorum, Türkiye.

**ABSTRACT** This study presents a TinyML-based machine learning system for multi-class ear condition classification on an edge device, designed to process images captured from a digital otoscope camera. Utilizing a dataset comprising five categories, Normal, Acute Otitis Media (AOM), Cerumen Impaction (CI), Chronic Otitis Media (COM), and Myringosclerosis (MYS), the proposed system performs near real-time classification directly on a resource-constrained microcontroller. The model was developed and optimized using the Edge Impulse platform and deployed as a quantized TinyML library. The system architecture incorporates lightweight convolutional neural networks (CNNs) and the EON™ Compiler to ensure efficient memory usage while maintaining high diagnostic performance. Experimental results demonstrate a validation accuracy of 97.5% and a testing accuracy of 96.31%, with a peak RAM footprint of only 240.3K and an inferencing latency of 1482 ms. These findings highlight the potential of TinyML for portable, low-power medical applications, providing a foundation for privacy-preserving, GDPR-compliant, on-device diagnostics in auditory healthcare without reliance on cloud infrastructure.

**KEYWORDS**
Ear conditions
TinyML
Multi-class classification
Edge impulse
Otoscope camera

## INTRODUCTION

Ear diseases represent a significant clinical challenge due to their high prevalence worldwide and the complexity of achieving accurate diagnosis through visual examination. Common otoscopic findings such as Acute Otitis Media (AOM), Chronic Otitis Media (COM), Cerumen Impaction (CI), and Myringosclerosis (MYS) affect diverse populations and may lead to pain, hearing loss, and long-term complications if not diagnosed and treated promptly. Traditional clinical diagnosis of these ear conditions primarily relies on otoscopic examination performed by specialists, which involves visual inspection of the tympanic membrane and ear canal. Although this method is widely adopted in clinical practice, it is inherently subjective and highly dependent on clinician expertise, resulting in variability in diagnostic accuracy, particularly in primary care settings where access to otolaryngology specialists may be limited (Al-Rahim Habib *et al.* 2022; Livingstone and Chau 2020).

The limitations of traditional diagnostic procedures have motivated the exploration of advanced computational methods. In particular, artificial intelligence (AI) and machine learning (ML) approaches have shown promise in automating image based diagnosis of ear disorders. Systematic reviews indicate that AI algorithms, especially convolutional neural networks (CNNs), can achieve high classification accuracy for otoscopic images, often surpassing non expert human performance. For example, AI-based methods have reported classification accuracies of up to 97.6% in multiclass tasks distinguishing normal conditions, acute otitis media (AOM), and otitis media with effusion using otoscopic images (Tatlı 2025; Song *et al.* 2022). Recent studies have begun exploring transformer-inspired feature representations for otoscopic image analysis, aiming to enhance global contextual understanding and feature extraction beyond conventional convolutional architectures (Demircan *et al.* 2025).

However, these AI-driven systems often rely on deep learning models executed on high-performance hardware or cloud services, which introduces latency, dependency on network connectivity, and privacy concerns, limiting their practicality in resource-constrained or portable environments (Diez *et al.* 2024). Furthermore, while high-performance models like YOLOv10 are emerging for real-time mobile endoscopy, they still demand substantial computational overhead compared to ultra-low-power edge solutions (Wang *et al.* 2024).

To overcome these limitations, Tiny Machine Learning (TinyML) has emerged as a key technology for low-power, on-device AI applications on embedded and edge devices. TinyML enables real-time inference directly on microcontrollers and other embedded hardware, reducing latency, preserving privacy, and operating independently from external servers (Heydari and Mahmoud 2025; Schizas *et al.* 2022). Platforms such as Edge Impulse facilitate the design, training, optimization, and deployment of TinyML models for embedded tasks, including image classification on resource-constrained devices. Recent studies and platform evaluations indicate that tools such as the EON Tuner allow these models to maintain clinically relevant accuracy while fitting within the strict memory limits of Cortex-M microcontrollers (Hymel *et al.* 2022).

**Manuscript received:** 17 November 2025,
**Revised:** 14 January 2026,
**Accepted:** 20 January 2026.

[1]serkandislitas@hitit.edu.tr (**Corresponding author**)

Despite these advances, the application of TinyML for multi-class ear condition classification remains underexplored. While prior studies demonstrate the potential of machine learning for diagnosing ear disorders using deep learning, most focus on computationally intensive models that require cloud or Graphics Processing Unit (GPU) resources (Tatlı 2025; Song *et al.* 2022; Bingol 2022). Therefore, there is a clear need for research combining lightweight ML models, edge computing, and embedded platforms for real-time, on-device classification. In this study, we propose a TinyML-based machine learning system for multi-class ear condition classification deployable on edge devices. Using a publicly available dataset covering five categories, Normal, AOM, CI, COM, and MYS this work demonstrates the design, training, optimization, and deployment of TinyML models with Edge Impulse, offering portable, low-power auditory diagnostics for clinical support.

## RELATED WORKS

Automated diagnosis of ear diseases using machine learning has rapidly expanded. Deep learning approaches, especially CNN-based models, have demonstrated high performance for multi-class otoscopic and tympanic membrane image classification, often surpassing non-expert human performance (Tatlı 2025; Song *et al.* 2022; Bingol 2022). Advanced CNN pipelines with hyperparameter optimization, data augmentation, and ensemble methods have achieved accuracies above 98% across multiple ear disease categories (Bingol 2022; Mihigo *et al.* 2022). TinyML applications have extended this capability to embedded edge devices. Visual TinyML applications using Edge Impulse have successfully employed compact cameras, such as otoscope modules, for real-time multi-class classification tasks. For instance, hand posture recognition, finger number detection, and tomato leaf disease identification illustrate that highly constrained devices can perform accurate classification (Heydari and Mahmoud 2025; Kwon 2023). These studies demonstrate the feasibility of deploying TinyML models for real-time, edge-based decision-making.

In healthcare, TinyML has been applied to both audio and visual modalities. Cough detection systems and on-device speech recognition employ lightweight feature extraction and optimized neural networks trained on Edge Impulse, achieving real-time, low-power inference without cloud dependency (Rana *et al.* 2022; Kwon 2023). Specifically in otolaryngology, studies on otoscopic and tympanic membrane images have explored anomaly detection and disease classification using both deep learning and TinyML approaches on otoscopic and endoscopic images (Tatlı 2025; Song *et al.* 2022; Bingol 2022). To address the limitations of static models, adaptive quantization strategies are now being developed specifically for medical wearables to maintain accuracy under extreme energy constraints (Xie and Fang 2025). Beyond medical applications, TinyML has been used for IoT and time series tasks, including predictive maintenance and environmental monitoring. Lightweight network architectures such as TinyLSTM and TinyModel have been deployed on embedded devices via Edge Impulse, demonstrating real-time inference and energy efficiency for sequential data (Mihigo *et al.* 2022; Cioflan *et al.* 2025). These studies highlight TinyML's domain-agnostic capabilities, supporting visual, auditory, and time series data on resource-constrained devices.

Despite these advances, several challenges remain in the deployment of TinyML systems. Existing literature identifies model optimization, memory management, hardware compatibility, benchmarking, and the lack of standardization as key areas requiring further improvement (Heydari and Mahmoud 2025; Schizas *et al.* 2022). In real-time medical applications, maintaining high accuracy, reliability, and low inference latency under strict energy constraints is particularly critical (Bingol 2022). Furthermore, the integration of Explainable Artificial Intelligence (XAI), including both visual explanation techniques and medical-oriented interpretability frameworks, is increasingly recognized as essential for enhancing clinical interpretability and trust in automated otoscopic diagnostic systems (Rehman *et al.* 2025; Özdilli *et al.* 2025; Tjoa and Guan 2020).

In summary, existing literature confirms that TinyML is effective for edge-based multi-class classification and anomaly detection, particularly in healthcare. However, challenges related to data diversity and model optimization remain in medical visual classification. Motivated by these gaps, the present study focuses on multi-class classification of ear conditions using TinyML, leveraging Edge Impulse optimized models deployed on microcontroller-based edge devices, extending existing visual TinyML applications to low-power medical classification on edge devices.

## MATERIAL AND METHODS

The methodology of this study focuses on the design, training, and deployment of a TinyML-based machine learning model for multi-class classification of ear conditions, leveraging the Edge Impulse platform. This approach integrates modern machine learning techniques with embedded systems, enabling real-time, on-device inference on an edge device.

### Dataset

In this study, a publicly available otoscopic image dataset obtained from the Kaggle (Uci Machine Learning Repository 2025) platform was used for training and evaluating the proposed TinyML-based inner ear condition classification system. The dataset consists of labeled otoscopic images representing five clinically relevant classes: Normal, AOM, CI, COM, and MYS. These categories were selected to cover a spectrum of otoscopic findings commonly encountered in clinical practice. The dataset includes color images acquired under varying illumination conditions and viewpoints, reflecting real-world variability in otoscopic examinations. As the dataset is publicly accessible and anonymized, no ethical approval or patient consent was required. Prior to model training, the dataset was uploaded to the Edge Impulse platform, where it was automatically partitioned into training and test subsets using an 80/20 split. This partitioning strategy was specifically chosen because the dataset maintains a balanced distribution across all five categories, ensuring that the test results provide a statistically significant representation of the model's generalizability. This randomized selection process ensures an unbiased evaluation of model performance and minimizes the risk of overfitting by validating the system on previously unseen data that reflects the overall composition of the dataset.

The dataset is balanced across the five categories, with approximately 600 images per class. In total, the dataset consists of 2978 images, of which 2391 were used for training and 597 for testing. The balanced distribution reduces the risk of biased learning and enhances classification performance. The detailed distribution of images across classes and data splits is summarized in Table 1. Representative sample images from each ear condition class are illustrated in Figure 1, demonstrating the visual characteristics and intra-class variability present in the dataset.

**Table 1** Distribution of otoscopic images in the Kaggle dataset for inner ear condition classification (Uci Machine Learning Repository 2025)

| Class Label | Inner Ear Condition | Training | Test | Total |
|---|---|---|---|---|
| C1 / Normal | Normal | 480 | 120 | 600 |
| C2 / AOM | Acute Otitis Media (AOM) | 463 | 115 | 578 |
| C3 / CI | Cerumen Impaction (CI) | 480 | 120 | 600 |
| C4 / COM | Chronic Otitis Media (COM) | 479 | 121 | 600 |
| C5 / MYS | Myringosclerosis (MYS) | 479 | 121 | 600 |
| | Grand Total | 2391 | 597 | 2978 |

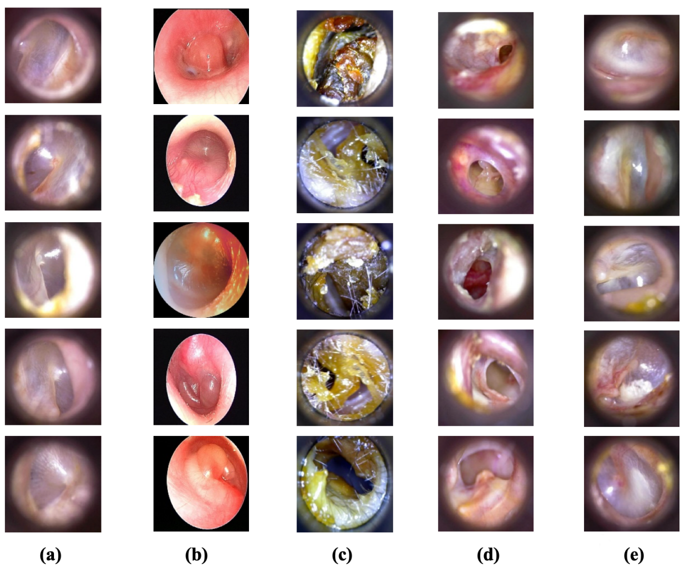


**Figure 1** Representative otoscopic images from the dataset illustrating the five ear condition classes: (a) Normal, (b) AOM, (c) CI, (d) COM, and (e) MYS (Uci Machine Learning Repository 2025).

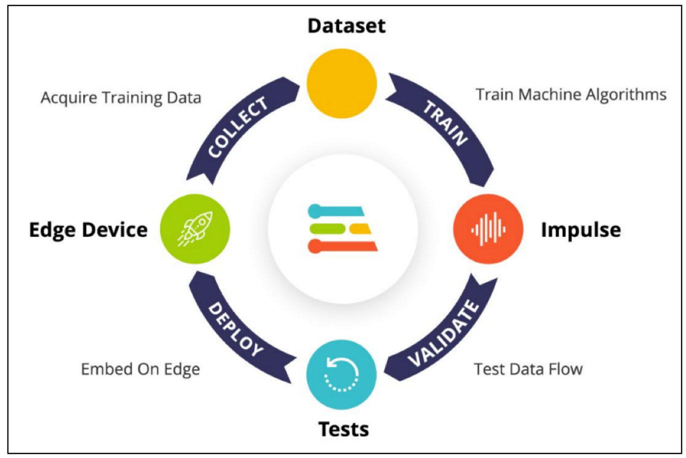


**Figure 2** The end-to-end TinyML development workflow in Edge Impulse.

### TinyML model design using Edge Impulse Platform

Edge Impulse is a comprehensive development platform specifically engineered for TinyML, providing a unified end-to-end workflow to design, optimize, and deploy machine learning models on resource-constrained hardware (Edge Impulse 2025; Warden and Situnayake 2019), with the complete cycle of model training and edge device deployment depicted in Figure 2 (Rust 2020). This systematic approach allows developers to move seamlessly from raw data acquisition to real-time inference on embedded devices. The platform integrates advanced digital signal processing (DSP) for automated feature extraction with support for optimized neural network architectures, such as Convolutional Neural Networks (CNNs) (Han *et al.* 2015). By utilizing sophisticated optimization tools like quantization and the EON Compiler, Edge Impulse minimizes the memory footprint and latency of models, enabling efficient on-device inference (Moreau 2024). This framework ensures high performance and data privacy, making it ideal for real-time medical diagnostic systems on edge devices (Hizem *et al.* 2025).

## DESIGNED SYSTEM

### Proposed Model

The systematic development of the classification system, as illustrated in the flowchart in Figure 3, follows a structured pipeline within the platform. The process begins with the data acquisition stage, which utilizes a publicly available Kaggle dataset comprising 2,978 otoscopic images categorized into five clinically relevant classes: Normal, AOM, CI, COM, and MYS. In the data preprocessing stage, all images are resized to a standardized resolution of $96 \times 96$ pixels and normalized using Edge Impulse's built-in DSP blocks. This step ensures computational efficiency while preserving discriminative visual patterns. Additionally, to improve model robustness and generalization, data augmentation techniques such as rotation, flipping, and brightness adjustment are applied during this phase.

Following the dataset upload and train-test splitting, the feature extraction and neural network design stage employs a CNN-based architecture optimized for microcontroller constraints. During model training and optimization, hyperparameters are tuned on Edge Impulse servers, and critical quantization techniques are applied to minimize the memory footprint. After rigorous validation and testing via confusion matrices, precision, and recall, the optimized model is exported as a standalone C++ library compatible with the 32-bit microcontroller. The final stages involve the development of edge device firmware and its deployment, enabling the system to execute real-time inference and classification directly on the microcontroller.

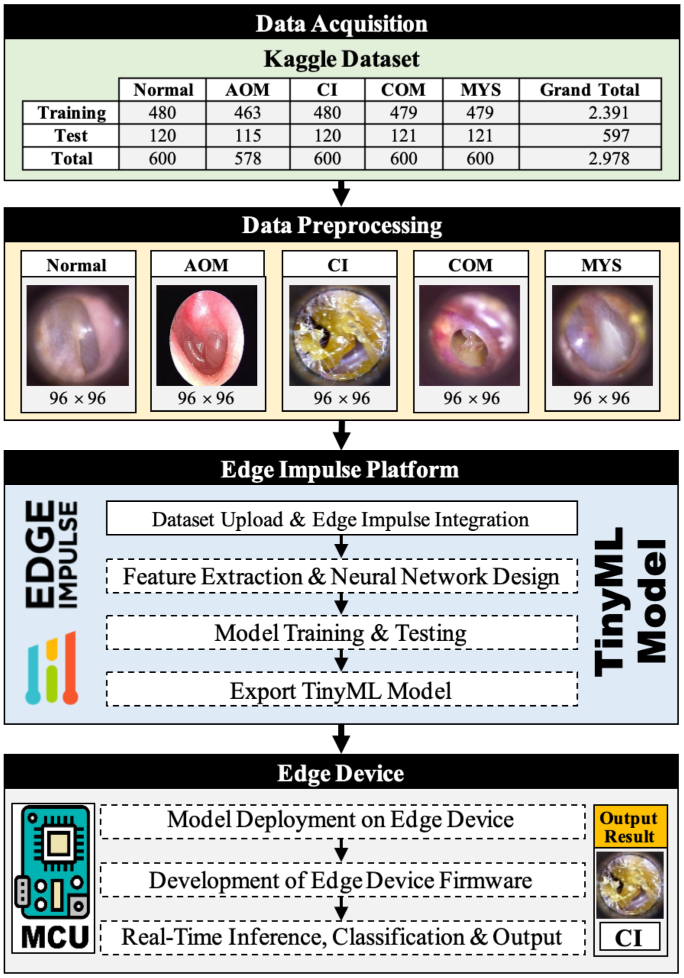


**Figure 3** Flowchart of the proposed TinyML model development for ear condition classification on the Edge Impulse platform.

The structured pipeline for the diagnostic system is depicted in Figure 4, showing the transition from raw otoscopic image input to the final classification of five distinct ear conditions. The architecture begins with an image data block where raw otoscopic images are processed with a predefined 96x96 pixel resolution, a resizing step crucial for balancing the extraction of clinical features with the memory constraints of the 32-bit microcontroller hardware. This is followed by an image processing block that transforms the data into a feature set optimized for the subsequent learning phase. Finally, a neural network classifier is utilized to categorize these processed features into five diagnostic classes: AOM, CI, COM, MYS, and Normal. By utilizing this modular Impulse Design, the system ensures a streamlined data flow specifically optimized for accurate, real-time diagnostic performance on edge devices.

The core of this project is the deployment of a robust diagnostic system on a resource-constrained microcontroller. As shown in Table 2, the training settings were specifically tuned for the 32-bit microcontroller. By employing a 0.0005 learning rate and INT8 quantization, the system provides real-time, on-device classification of ear conditions such as AOM, COM, CI, and MYS. This optimization ensures that the final model maintains a minimal memory footprint suitable for edge deployment while delivering high diagnostic accuracy for clinical decision support.

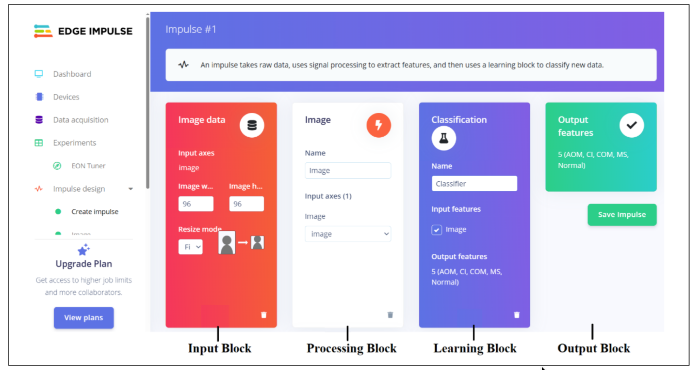


**Figure 4** The impulse design and processing pipeline for otoscopic ear disease classification.

**Table 2** Neural network training configuration and optimization settings for the TinyML-based ear disease classification project

| Training Setting | Value/Status |
|---|---|
| Number of epochs | 50 |
| Learning Rate | 0.0005 |
| Training Processor | CPU |
| Validation Set Size | 20% |
| Batch Size | 32 |
| Profile int8 Model | Active |

The neural network architecture designed for the classification task is illustrated in Figure 5, featuring a Convolutional Neural Network (CNN) structure optimized for deployment on the 32-bit microcontroller. The model begins with an input layer processing 27648 features, derived from the 96 x 96 pixel input, which is then organized by a reshape layer. Feature extraction is performed through two successive stages of 2D convolutional and pooling layers, utilizing 32 filters in the first stage and 64 filters in the second, both with a 3 x 3 kernel size. To improve model generalization and prevent overfitting, two dropout layers with a rate of 0.25 are strategically integrated after the convolutional blocks. Finally, a flatten layer converts the multidimensional feature maps into a 1D vector to enable the final classification of ear conditions.

### Designed Embedded System

The block diagram of the proposed TinyML-based ear condition classification system is illustrated in Figure 6. The architecture follows a sequential and modular pipeline, ensuring efficient real-time diagnostics on resource-constrained hardware.

The process begins with the Input (Camera Module) block, where an otoscope camera, supported by integrated LED illumination, captures images of the ear canal and tympanic membrane. These captured otoscopic images are transmitted directly to the Embedded Processing Unit (Edge Device / microcontroller), which serves as the central hub for local data processing. Within this unit, the Image Preprocessing stage executes resizing, noise reduction, and normalization to optimize the visual data for neural network analysis. Subsequently, the processed data is passed to the TinyML Inference Engine, utilizing an optimized model trained via Edge

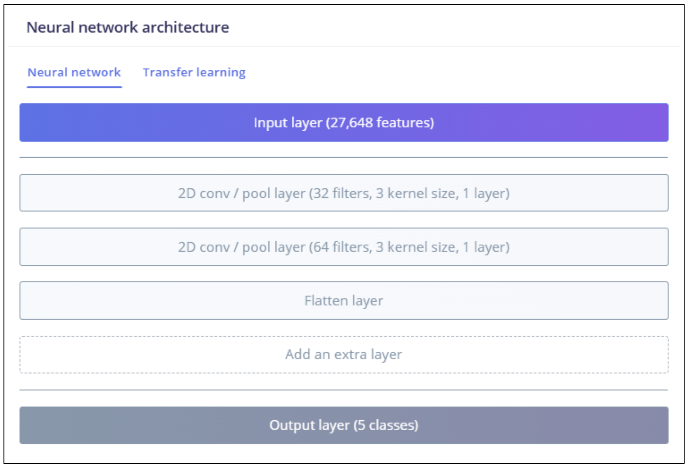


**Figure 5** The neural network architecture of the TinyML model for otoscopic image classification.

Impulse.

The engine performs on-device classification, and the resulting Classified Output is forwarded to the final Output (Interface) block. This interface displays the identified class such as Normal, AOM, CI, COM, or MYS and provides diagnostic decision support along with confidence scores. By executing the entire pipeline locally, the system eliminates the need for cloud-based computation, thereby ensuring low latency and maintaining strict data privacy for point-of-care medical applications.

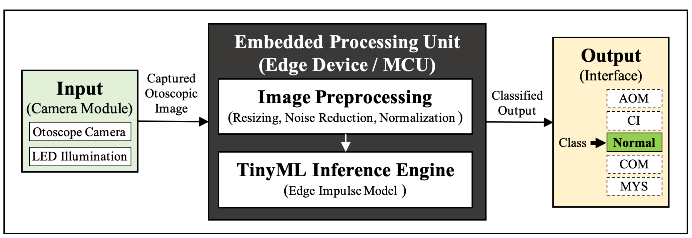


**Figure 6** The block diagram of the proposed TinyML-based ear condition classification system.

As illustrated in Figure 7, the proposed TinyML-based inner ear condition classification system operates using a sequential and loop-based software flow. The process begins with system initialization, during which the embedded controller, camera module, and the pre-trained TinyML model generated using the Edge Impulse platform are loaded and configured. At this stage, camera illumination parameters are also initialized to ensure consistent lighting conditions during image acquisition.

Following initialization, the system captures an otoscopic image using the camera module under controlled illumination. The acquired image is then forwarded to the Edge Impulse image processing pipeline, where essential pre-processing operations such as resizing and normalization are applied. These steps prepare the image for efficient inference on resource-constrained embedded hardware.

Subsequently, the pre-processed image is passed to the TinyML inference engine, which classifies the image into one of the predefined ear condition classes: Normal, AOM, CI, COM, and MYS. The classification result is then presented to the user via an output interface such as LEDs, a display module, or serial communication. After a predefined waiting period, the system either captures the next image or returns to an idle state, enabling continuous or on-demand operation of the diagnostic system.

Overall, the proposed software workflow enables a low-power, real-time, and robust TinyML-based implementation on a microcontroller, supporting portable and efficient classification of ear conditions.

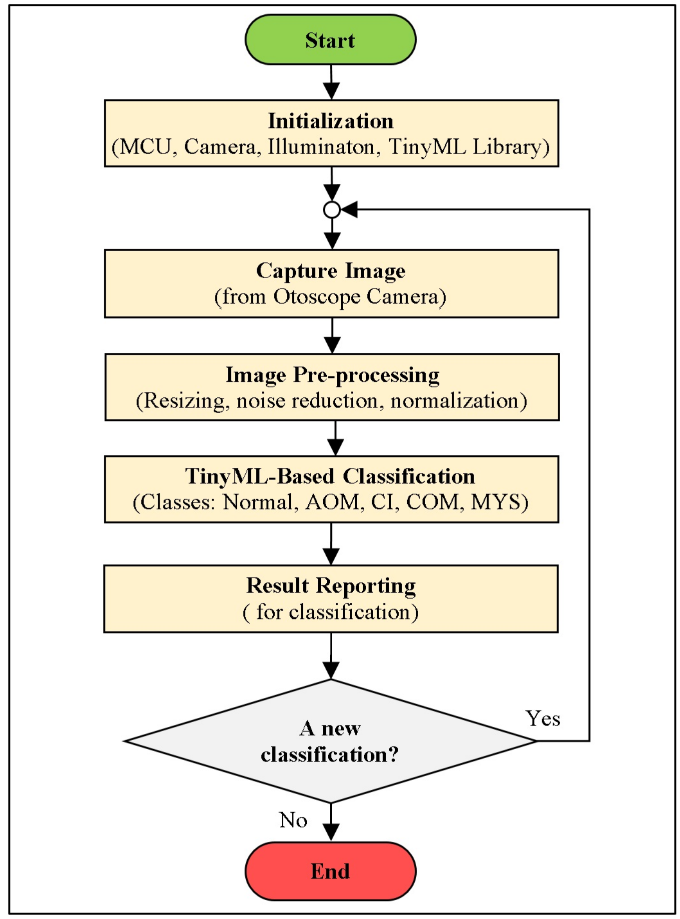


**Figure 7** Software flowchart of the proposed TinyML-based ear condition classification system incorporating controlled camera illumination and Edge Impulse-based image processing.

## RESULTS AND DISCUSSION

The performance of the proposed TinyML system for ear condition classification was evaluated using a comprehensive set of metrics, including accuracy, sensitivity, precision, and F1-score. These metrics, calculated from the validation set's confusion matrix, serve as a vital framework for assessing the model's diagnostic reliability in medical imaging. Accuracy measures the overall proportion of correct classifications, while sensitivity determines the model's ability to correctly identify true positive cases. Precision assesses the reliability of positive predictions, and the F1-score provides a balanced evaluation by calculating the harmonic mean of precision and sensitivity. The mathematical definitions for these metrics are presented in Equations (1–4), forming the basis for the 97.5% accuracy achieved in this study. In these equations, TP (True Positives) and TN (True Negatives) represent correctly classified instances, while FP (False Positives) and FN (False Negatives) denote the

**Table 3** Performance metrics of the TinyML-based ear disease classification system

| Classes | Accuracy (%) | Precision | Sensitivity | F1-Score |
|---|---|---|---|---|
| AOM | 97.5 | 1.00 | 1.00 | 1.00 |
| CI | 97.5 | 1.00 | 1.00 | 1.00 |
| COM | 97.5 | 0.97 | 0.98 | 0.98 |
| MYS | 97.5 | 0.96 | 0.93 | 0.94 |
| Normal | 97.5 | 0.95 | 0.97 | 0.96 |
| Average | 97.5 | 0.98 | 0.98 | 0.98 |

misclassified instances (Alaca and Akmeşe 2025; Fawcett 2006).

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{F-score} = \frac{2 * TP}{2 * TP + FP + FN} \tag{4}$$

The diagnostic performance of the proposed TinyML system is quantitatively summarized in Table 3, which highlights the model's high classification efficacy across five distinct ear conditions. According to the data, the system achieved a robust overall accuracy of 97.5% with a consistent total precision, sensitivity, and F1-score of 0.98. Specifically, the AOM and CI categories demonstrated perfect classification performance with F1-scores of 1.00. While the MYS class exhibited the lowest relative sensitivity at 0.93 due to minor inter-class confusion with the Normal category, the overall high metrics across all labels validate the reliability of the optimized neural network for near real-time, on-device medical diagnostics as defined by Equations (1–4).

As illustrated in Figure 8, high values along the diagonal of the confusion matrix indicate strong classification accuracy. The on-device performance metrics, shown in Figure 9, demonstrate the model's efficiency on 32-bit microcontrollers. Utilizing the EON™ Compiler, the system achieves an inference time of 1482 ms, with a peak RAM usage of 240.3K and a flash usage of 243.1K.

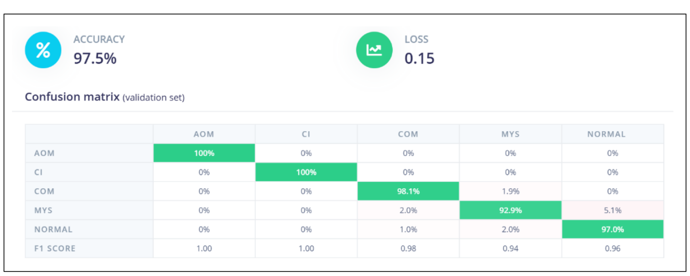


**Figure 8** Confusion matrix calculated by Edge Impulse for inner ear disease classification.

The spatial distribution is visualized in the Feature Explorer (Figure 10). The clear grouping of data points indicates that the feature extraction layers effectively identified unique patterns. Furthermore, the model achieved a perfect AUC of 1.00 as shown in Table 4, demonstrating high consistency across all categories. Finally, the model's testing phase on a separate dataset yielded an accuracy of 96.31% (Figure 11), confirming a robust and reliable classification system for otoscopic ear disease detection.

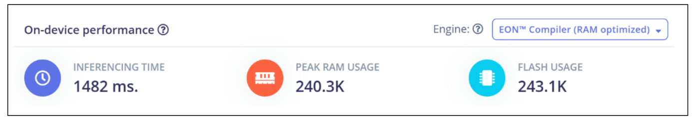


**Figure 9** On-device performance metrics for inner ear disease classification on 32-bit mcu, including inference time, peak RAM usage, and flash memory usage.

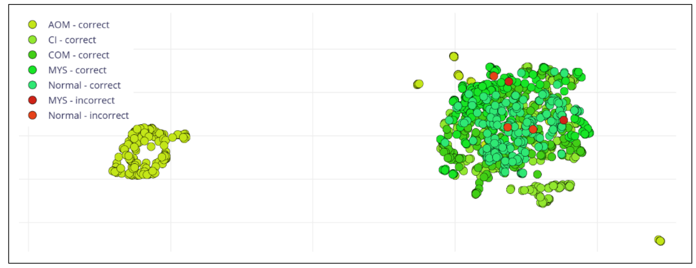


**Figure 10** Feature explorer visualization of the otoscopic image dataset, illustrating the spatial separation of disease classes (AOM, CI, COM, MYS, and Normal).

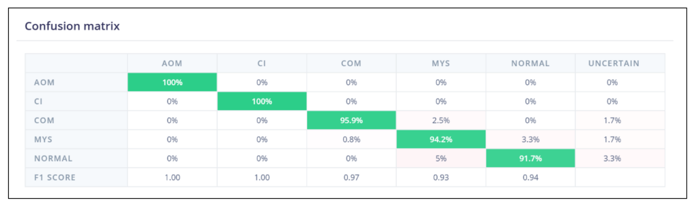


**Figure 11** Model testing results showing the confusion matrix and performance metrics for five-class otoscopic disease classification.

**Table 4** Validation metrics of the TinyML-based ear disease classification system

| Metrics | Value |
|---|---|
| Area under ROC Curve | 1.00 |
| Weighted average Precision | 0.97 |
| Weighted average Recall | 0.97 |
| Weighted average F1 score | 0.97 |

The proposed system enhances patient privacy by performing all inferences locally on the microcontroller, ensuring compliance with data protection regulations (e.g., GDPR) as no raw data is transmitted to the cloud. Designed as a rapid point-of-care screening tool, the device provides immediate feedback in resource-limited settings. While this proof-of-concept is promising, future transition to clinical use will require formal certifications (e.g., FDA or CE MDR) and real-world clinical trials to validate its diagnostic efficacy and workflow integration.

## CONCLUSION

This study successfully demonstrated the implementation and deployment of a TinyML-based diagnostic system for the multi-class classification of ear diseases on resource-constrained 32-bit microcontrollers. By leveraging the Edge Impulse platform and lightweight convolutional neural networks, the proposed system achieved a robust validation accuracy of 97.5% with a minimal loss of 0.15. Final testing on a separate dataset further confirmed the model's reliability, yielding a performance accuracy of 96.31%. The model exhibited exceptional precision in identifying AOM and CI categories with perfect F1-scores of 1.00, proving its effectiveness in distinguishing high-priority pathological conditions from normal otoscopic findings.

The technical evaluation highlights the system's high efficiency for edge computing. Utilizing the EON™ Compiler, the architecture was optimized to operate within the physical memory limits of embedded hardware, maintaining a peak RAM usage of 240.3K and a flash footprint of 243.1K. With an inference time of 1482 ms, the system enables near-instantaneous, on-device diagnostics without the latency, network dependency, or privacy risks associated with cloud-based AI solutions. While minor misclassification patterns were noted specifically where 5.1% of MYS cases were identified as Normal the overall aggregate F1-score of 0.98 validates the system as a robust tool for clinical support in real-world scenarios.

In conclusion, this research establishes a scalable and low-power framework for auditory healthcare diagnostics. By enabling automated and objective ear examinations directly on portable devices, this TinyML approach offers a viable solution for primary care settings and regions with limited access to otolaryngology specialists. Future work will focus on expanding the dataset to include a wider variety of pathological stages and further optimizing the model to reduce inference time on even lower-power 32-bit hardware. This study bridges the gap between complex deep learning models and practical, on-device intelligence, marking a significant step forward in the democratization of advanced medical diagnostic tools.

### Ethical standard

The author has no relevant financial or non-financial interests to disclose.

### Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

### Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

## LITERATURE CITED

Al-Rahim Habib, A., M. Faruque, and A. M. Islam, 2022 Artificial intelligence to classify ear disease from otoscopy: A systematic review and meta-analysis. Clinical Otolaryngology **47**: 1354–1365.

Alaca, Y. and Ö. F. Akmeşe, 2025 Pancreatic tumor detection from ct images converted to graphs using whale optimization and classification algorithms with transfer learning. International Journal of Imaging Systems and Technology **35**: e70040.

Bingol, H., 2022 Classification of ome with eardrum otoendoscopic images using hybrid-based deep models, nca, and gaussian method. Traitement du Signal **39**.

Cioflan, C., J. Fonseca, X. Wang, and L. Benini, 2025 Nanohydra: Energy-efficient time-series classification at the edge. arXiv preprint arXiv:2510.20038 .

Demircan, F., M. Ekinci, Z. Cömert, and E. Gedikli, 2025 Enhanced classification of ear disease images using metaheuristic feature selection. Sakarya University Journal of Computer and Information Sciences **8**: 58–75.

Diez, P. L., J. V. Sundgaard, J. Margeta, K. Diab, F. Patou, *et al.*, 2024 Deep reinforcement learning and convolutional autoencoders for anomaly detection of congenital inner ear malformations in clinical ct images. Computerized Medical Imaging and Graphics **113**: 102343.

Edge Impulse, 2025 Edge impulse documentation. Accessed: Sep. 01, 2025.

Fawcett, T., 2006 An introduction to roc analysis. Pattern Recognition Letters **27**: 861–874.

Han, S., H. Mao, and W. J. Dally, 2015 Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. arXiv preprint arXiv:1510.00149 .

Heydari, S. and Q. H. Mahmoud, 2025 Tiny machine learning and on-device inference: A survey of applications, challenges, and future directions. Sensors **25**: 3191.

Hizem, M., L. Bousbia, Y. Ben Dhiab, M. O. E. Aoueileyine, and R. Bouallegue, 2025 Reliable ecg anomaly detection on edge devices for internet of medical things applications. Sensors **25**: 2496.

Hymel, S., C. Banbury, D. Situnayake, A. Elium, C. Ward, *et al.*, 2022 Edge impulse: An mlops platform for tiny machine learning. arXiv preprint arXiv:2212.03332 .

Kwon, C. K., 2023 Development of embedded machine learning finger number recognition application using edge impulse platform. In *2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE)*, pp. 2697–2699, IEEE.

Livingstone, D. and J. Chau, 2020 Otoscopic diagnosis using computer vision: An automated machine learning approach. The Laryngoscope **130**: 1408–1413.

Mihigo, I. N., M. Zennaro, A. Uwitonze, J. Rwigema, and M. Rovai, 2022 On-device iot-based predictive maintenance analytics model: Comparing tinylstm and tinymodel from edge impulse. Sensors **22**: 5174.

Moreau, L., 2024 Introducing: Eon compiler ram-optimized. Accessed: Sep. 01, 2025.

Özdilli, Ö., S. Şevik, Y. Alaca, and Y. Uzunoğlu, 2025 Optimal design of flat plate fin heat sinks using a computational fluid dynamics (cfd) and deep learning (dl)-based ensemble approach with explainable artificial intelligence (xai) integration. Applied Thermal Engineering p. 127547.

Rana, A., Y. Dhiman, and R. Anand, 2022 Cough detection system using tinyml. In *2022 International Conference on Computing, Communication and Power Technology (IC3P)*, pp. 119–122, IEEE.

Rehman, Z. U., M. F. A. Fauzi, F. N. I. Lokman, M. Touhami, and L. Saim, 2025 Efficient and interpretable otoscopic image classification via distilled cnn with adaptive channel attention. IEEE Access .

Rust, E., 2020 Getting started with edge impulse. Accessed: Dec. 03, 2025.

Schizas, N., A. Karras, C. Karras, and S. Sioutas, 2022 Tinyml for

ultra-low power ai and large scale iot deployments: A systematic review. Future Internet **14**: 363.
Song, D., I. S. Song, J. Kim, J. Choi, and Y. Lee, 2022 Semantic decomposition and anomaly detection of tympanic membrane endoscopic images. Applied Sciences **12**: 11677.
Tatlı, Y., 2025 Ear pathologies using deep learning on otoscopic images. Uluslararası Sürdürülebilir Mühendislik ve Teknoloji Dergisi **9**: 51–57.
Tjoa, E. and C. Guan, 2020 A survey on explainable artificial intelligence (xai): Toward medical xai. IEEE Transactions on Neural Networks and Learning Systems **32**: 4793–4813.
Uci Machine Learning Repository, 2025 Otoscopic image dataset. Kaggle, Accessed: Dec. 03, 2025.
Wang, A., H. Chen, L. Liu, K. Chen, Z. Lin, *et al.*, 2024 Yolov10: Real-time end-to-end object detection. Advances in Neural Information Processing Systems **37**: 107984–108011.
Warden, P. and D. Situnayake, 2019 *TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers*. O'Reilly Media.
Xie, Y. and Q. Fang, 2025 An energy-aware generative ai edge inference framework for low-power iot devices. Electronics **14**: 4086.

***How to cite this article:*** Dişlitaş, S. TinyML-Based Machine Learning System for Multi-Class Ear Condition Classification. *Computers and Electronics in Medicine*, 3(1), 86-93, 2026.