Instituto Federal de Educação, Ciência e Tecnologia de São Paulo
Laboratório Maxwell de Micro-ondas e Eletromagnetismo Aplicado
Anais do Workshop de Micro-ondas DOI: 10.5281/zenodo.10051682 ISSN 2675-4460

SOUND DETECTION IN THE ICU WITH TINYML: PROJECT WITH ARDUINO NANO 33 BLE SENSE AND EDGE IMPULSE

Vinicius Belo Da Silva Rayche Dos Santos[1], Amanda Trindade de Santana Elisiario[1], João Victor De Souza Prado Siqueira[1], Muniz Almeida Costa[1], Fabio da Silva Moraes[2], Dr. Arnaldo de Carvalho Junior[1], Dr. Walter Augusto Varella[1]
[1]Federal Institute of Education, Science and Technology of São Paulo, Cubatão Campus.
[1]{vinicius.rayche, e.trindade, j.siqueira, muniz }@aluno.ifsp.edu.br and {adecarvalhojr,varella}@ifsp.edu.br.
[2]Flextronics Institute of Technology – Sorocaba
[two]fabio.moraes@fit-tecnologia.org.br

Summary- This article presents an early warning system for critical events in intensive care units (ICUs). The system uses sound detection techniques with TinyML to quickly identify potentially dangerous events such as suction noises, falls, and cardiac arrests.

Keywords: Sound detection; Artificial Intelligence in Health; TinyML; ICU.

INTRODUCTION

With technological advances in medical care for critically ill patients, intensive care units (ICUs) have become highly complex work environments [1]. However, this complexity also brings challenges such as noise levels [2] and alarm fatigue [3], and the presence of monitoring and life support equipment, together with the traffic of support personnel due to false alarms generated, results in dissatisfaction and discomfort for healthcare professionals and patients in the ICU [2]. Sound detection in the ICU can be vital, providing valuable information for monitoring and medical decision-making [1].

The Tiny Machine Learning (TinyML) research field offers a solution for such challenge. TinyML enables implementing machine learning models on embedded devices with scarce resource, as the development kit Arduino Nano 33 BLE Sense [4], here referred as Prototype. Using Edge Impulse, a leading platform for TinyML development [4], it is possible to train and deploy efficient models for detecting existing sounds in ICU environments.

This article aims to present a project that combines sound detection in the ICU with artificial intelligence techniques using the Prototype and Edge Impulse [4]. Through this approach, we seek to improve patient comfort and safety in the hospital environment [1], allowing the detection of sounds in the ICU, which may be equipment alarms or human traffic. Furthermore, this work can contribute to state-of-the-art research and innovation in intensive care [1].

This study builds on previous research that demonstrated the potential of TinyML in detecting and classifying environmental sounds [4][5]. However, by focusing specifically on ICU sounds, we hope to provide relevant insights that can help improve patient care by healthcare professionals.

LITERATURE REVIEW

This article's literature review focuses on four main areas: the complexity and challenges of ICUs, the emerging field of TinyML, the application of TinyML in sound detection and classification, and Edge Impulse.

A. Complexity and Challenges of ICUs

ICUs are highly complex work environments equipped with advanced technology to monitor critically ill patients. However, this complexity also brings noise levels, which can cause dissatisfaction and discomfort for patients and healthcare professionals. Sound detection in the ICU can provide vital information for monitoring and medical decision-making [1].

B. The Emerging Field of TinyML

TinyML is a solution that enables the use of machine learning on embedded systems with limited hardware resources, and with this comes an emerging field of new applications with low-cost hardware, integration of data collection through sensors, and action faster response to events, reducing latency in communication networks. Project development using machine learning techniques, model training, and testing carried out on Edge Impulse in a cloud environment with a large processing capacity. After the developed model presents the desired accuracy, low-cost hardware such as the sound and alarm detection system [4] is used.

C. Application of TinyML in Sound Detection and Classification

This study builds on previous research that demonstrated the potential of TinyML in detecting and classifying environmental sounds [4]. By focusing specifically on ICU sounds, we hope to provide valuable insights that can help improve patient care and the work environment for healthcare professionals.

D. Edge Impulse

Edge Impulse is an online tool for data collection, deep learning models training, and deployment of said models on edge computing and embedded and devices, enabling us to quickly solve the previously mentioned problems, as shown in Fig. 1 [6].

Instituto Federal de Educação, Ciência e Tecnologia de São Paulo
Laboratório Maxwell de Micro-ondas e Eletromagnetismo Aplicado
Anais do Workshop de Micro-ondas DOI: 10.5281/zenodo.10051682 ISSN 2675-4460

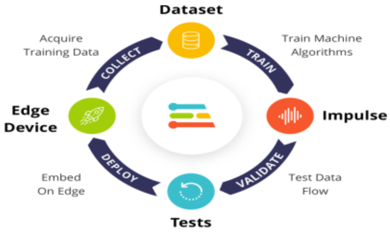

Figure 1 – Process carried out by Edge Impulse [8]

MATERIALS AND METHODS

Sound detection was integrated into the system using TinyML techniques. The Prototype collects and process the audio data locally. We trained a machine learning model was trained to identify adverse events [3], such as suction noises, falls, and cardiac arrests.

To collect data on sounds, present in the Intensive Care Unit (ICU), they were made available by the Kaggle platform [7], which has several directories. The selection of sounds met specific criteria, such as the functioning of medical equipment and healthcare professionals' interaction with patients.

Training the machine learning model used an audio dataset of 600 samples. The dataset included samples of all critical events the system was supposed to detect.

Edge Impulse was used as a tool for selecting relevant sounds and standardizing data to ensure the consistency of the sounds obtained and involved normalizing volumes and applying filters to remove background noise that could interfere with the analysis of ICU sounds.

Data pre-processing techniques were applied, such as normalization, filtering, and extracting relevant features, to improve the effectiveness and quality of the artificial intelligence models.

For the classifier model made in Edge Impulse, the sounds were divided into "Environmental Sounds" and "Alert," as shown in Fig. 2.

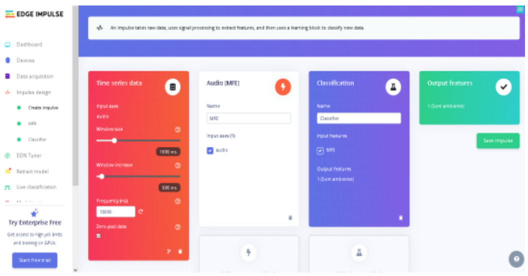

Figure 2 – Project momentum [8].

The sound detection models were trained with pre-processed training data, using convolutional neural network (CNN) techniques and classification algorithms, adjusting the parameters according to the problem.

Fig. 3 shows the Neural Network Architecture used and the parameters adjusted for the classifier model. The input layer uses a convolutional network with 16 filters by 3 in the kernel. The second layer is a layer with eight filters of size 3 in the kernel. The project has two output layers, one for each sound class. The loss rate 0.25 means that 25% of neurons are deactivated during training. After several iterations, the neural network learned to predict actions more accurately.

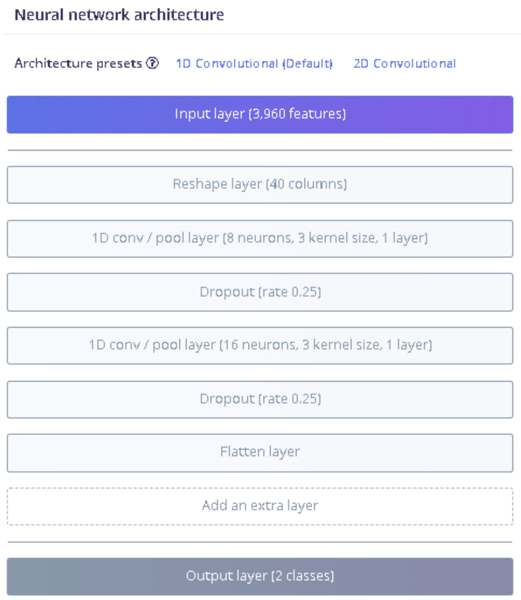

Figure 3– Neural Network Architecture used [8].

The machine learning model was deployed on the Prototype using the Edge Impulse platform. The Edge Impulse platform provides deploying and developing tools for machine learning models to edge devices.

The programming code on the Prototype hardware is done in the IDE developed by the Arduino company.

The Prototype hardware and the audio sensors were connected according to the manufacturer's specifications.

The code for reading the sensors used programming in Arduino, configuring the sampling rate and communication with Edge Impulse.

With this approach, the system implemented in the embedded system must then be subjected to accurate day-to-day data. It must compare the results obtained with those expected, thus enabling continuous system improvement.

RESULTS AND DISCUSSIONS

We carried out tests to validate sound detection in the ICU for adult patients with a capacity of eight beds in a public hospital. We consider different types of sounds relevant, such as medical equipment alarms, nurse calls, and critical events such as patient falls. The system developed using TinyML and Edge Impulse achieved a success rate of 65.52%, shown in Fig. 4, in identifying these sounds, with a low rate of false positives and false negatives, which can improve with appropriate database and microphone quality for collecting sounds. These results demonstrate the system's effectiveness in accurately detecting sounds in the ICU.

During testing, we identified some limitations such as the quality of the sounds used to train the model, the quality of the sound detection hardware, and the occurrence of environmental interference that could affect the detection quality. To mitigate these problems, we suggest using advanced signal

Instituto Federal de Educação, Ciência e Tecnologia de São Paulo
Laboratório Maxwell de Micro-ondas e Eletromagnetismo Aplicado
Anais do Workshop de Micro-ondas DOI: 10.5281/zenodo.10051682 ISSN 2675-4460

processing and filtering techniques and incorporating a more significant number of training samples to improve the robustness of the sound detection model.

Sound detection in the ICU enables faster actions in emergencies, ensures quality patient care, and minimizes risks. Also, consider that the sound detection system can learn from the day-to-day life of the ICU, making it even more adjusted to the environment.

The results demonstrate that the proposed model can meet the needs of sound detection in the ICU environment. The challenges of integrating the system with other medical devices and adapting to the conditions of each ICU are the following steps to be overcome.

Considering these results, the proposed approach can improve patient comfort and hospital safety in ICU environments.

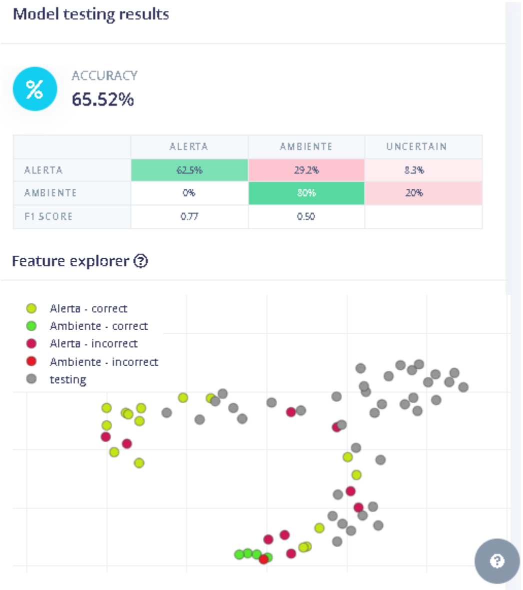

Figure 4 – Project testing [8]

REFERENCES

[1] SCHMIDT, S., DIEKS, JK., QUINTEL, M. et al. Development and evaluation of the focused assessment of sonographic pathologies in the intensive care unit (FASP-ICU) protocol. Crit Care 25, 405.https://doi.org/10.1186/s13054-021-03811-2. 2021.

[2] SCHMIDT, N., GERBER, SM, ZANTE, B. et al. Effects of intensive care unit ambient sounds on healthcare professionals: results of an online survey and noise exposure in an experimental setting. ICMx 8, 34.https://doi.org/10.1186/s40635-020-00321-3. 2020.

[3] APSF. Alarm fatigue and patient safety. Available in:https://www.apsf.org/pt-br/article/fadiga-de-alarme-e-seguranca-do-paciente/. Accessed on: Aug 14, 2023.

[4] KALLIMANI, R., PAI, K., RAGHUWANSHI, P. et al. TinyML: Tools, applications, challenges, and future research directions. Multimed Tools Appl.https://doi.org/10.1007/s11042-023-16740-9. 2023.

[5] VISWANATHA V., RAMACHANDRA AC, RAGHAVENDRA PRASANNA, PREM CHOWDARY KAKARLA, VIVEKA SIMHA PJ, NISHANT MOHAN. Implementation Of Tiny Machine Learning Models on Arduino 33 BLE For Gesture And Speech Recognition. Retrieved fromhttps://arxiv.org/abs/2207.12866v1. 2022.

[6] HYMEL, Shawn. et al. “Edge Impulse: An Mlops Platform for Tiny Machine Learning." Proceedings of the 6h MLSys Conference, Miami Beach, 2023.

[7] KAGGLE. Hospital Ambient Noise. Available in:https://www.kaggle.com/datasets/nafin59/hospital-ambient-noise. Accessed on September 14, 2023.

[8] EDGE IMPULSE. Edge Impulse. Available at: https://www.edgeimpulse.com/. Accessed on August 25, 2023.