# Challenge accepted

# Life-threatening ventricular arrhythmia detection challenge in implantable cardioverter–defibrillators

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**The organizers of the TinyML Design Contest describe the top machine-learning-based real-time detection algorithms for ventricular arrhythmia.**

Ventricular fibrillation and ventricular tachycardia are life-threatening ventricular arrhythmias (VAs) and the primary causes of sudden cardiac death, resulting in significant morbidity and mortality[1]. Individuals at high risk of sudden cardiac death rely on implantable cardioverter–defibrillators (ICDs) to provide timely and appropriate defibrillation treatment in case of life-threatening VAs[1]. However, existing industry practice is simple rule-based detection methods, which have not been updated over the past few decades[2,3]. Detection methods based on artificial intelligence (AI) and machine learning (ML) have demonstrated the potential to revolutionize ICD detection design by extracting features that may not be easily identifiable by human experts. AI/ML-based methods could improve the accuracy and efficiency of VA detection, thereby reducing the number of inappropriate shocks and improving the clinical outcomes of ICD recipients[4,5].

We organized the first TinyML contest in healthcare, the TinyML Design Contest (TDC), co-located at the 41st International Conference on Computer-Aided Design in 2022. TDC'22 was sponsored by the Association for Computing Machinery Special Interest Group on Design Automation, the Institute of Electrical and Electronics Engineers Council on Electronic Design Automation, and Singular Medical. More than 150 teams from over 50 organizations participated in TDC'22. TDC'22 motivated participating teams to design AI/ML algorithms and deploy them on ICDs. Specifically, the participants were asked to design and implement a working and open-source AI/ML algorithm that could automatically discriminate life-threatening VAs (i.e., using binary classification: VAs or
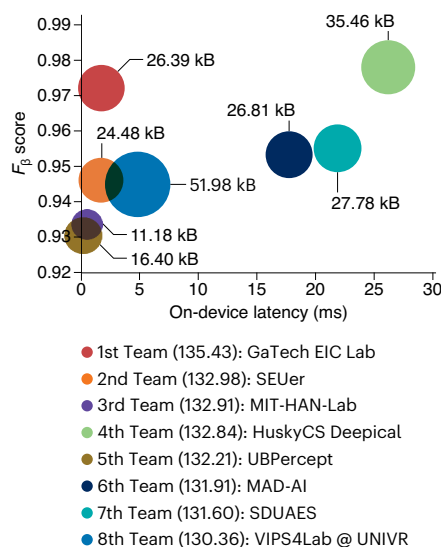


**Fig. 1 | Comprehensive performance metrics and the final scores of the top eight teams in TDC'22.** Metrics include $F_\beta$ by $y$ axis, inference latency by $x$ axis, and memory footprint by bubble size.

non-VAs) from other heart rhythms over intracardiac electrograms (IEGMs)[6]. Unlike in other healthcare challenges that focus only on detection accuracy, here we asked that the proposed AI/ML algorithm be able to be deployed and executed on an extremely low-power and resource-constrained microcontroller (MCU) such as are utilized in ICDs. The submitted designs were evaluated using comprehensive performance metrics: (1) detection performance, represented by $F_{\beta=2}$ score, which puts more weight on VA detection; (2) inference latency; and (3) memory occupation by the program of AI/ML algorithms. All of these metrics were measured on the MCU. The final score (out of 140) comprised a combination of detection performance, inference latency and memory footprint, with more weight placed on detection performance (with the weights of metrics 1–3 being 100, 20 and 20) because high detection accuracy is always the first priority in ICDs.

TDC'22 designated the NUCLEO-L432KC development kit (STMicroelectronics) as the targeting MCU platform for all participating teams. This $10 development board is equipped with an ARM Cortex-M4 core at 80 MHz, 256 kB of flash memory and 64 kB of SRAM, and its power consumption is around 30 mW in operation and 1.5 mW when idling. The IEGMs data were collected and provided by Singular Medical using ICDs. The whole dataset contains more than 38,000 IEGM segments with rhythm labels. The publicly released dataset includes over 30,000 IEGMs segments, while the testing dataset remained private for evaluation purposes. TDC'22 further provided a unified evaluation platform to evaluate the submitted design in terms of comprehensive metrics purely on board[7]. With the training dataset and unified evaluation platform, participating teams could utilize either the existing frameworks or their own tools to develop, train and deploy the AI/ML algorithm on board with cross-layer optimizations. With the great flexibility in algorithm design and deployment, the winning designs were very innovative (beyond deep learning) and could achieve results comparable to or even better than the current industry standards.

The ranking based on the final scores was released and the top eight teams were invited to receive the awards at the special sessions at the 41st International Conference on Computer-Aided Design. Fig. 1 shows the comprehensive performance metrics and the final scores of the top eight teams. The champion, GaTech EIC Lab, obtained 0.972 in $F_\beta$, 1.747 ms in latency and 26.39 kB in memory footprint with an elaborate deep neural network (DNN) structure design. Team GaTech EIC Lab used neural architecture search to automatically find the optimal convolutional neural network architecture. They further applied data augmentation to enrich the representation of training IEGM segments for better VA detection. The second-place team, SEUer, finished with 0.947 in $F_\beta$, 1.712 ms in latency and 24.48 kB in memory footprint, also with a DNN design. Team SEUer's solution was to manually and

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iteratively tune the network architecture design based on practical performances from evaluation. The third- and fifth-place teams, MIT-HAN-Lab and UBPercept, applied a decision tree model instead of DNN to reduce the program size and computation complexity, which achieve the lowest latency and memory footprint. Interestingly, as shown in Fig. 1, neither team achieved a high $F_\beta$ score because the conventional ML model could not fully address the drawback of the existing VA detection methods on ICDs due to the application of the manually extracted features. Another essential technique to improve detection accuracy is to invoke data augmentation in model training. Both HuskyCS Deepical (which was ranked first in $F_\beta$) and GaTech EIC Lab (ranked second in $F_\beta$) applied various signal augmentation techniques to enrich the representation of the provided IEGMs dataset. The contest problem, VA detection example, top eight team implementations and evaluation implementation can be accessed at https://tinymlcontest.github.io/TinyML-Design-Contest/index.html.

TDC'22 represented a platform for teams to exhibit their research and development work in the area of TinyML in healthcare and showcase the latest advancements. The future outlook for TinyML in healthcare has the goal of enabling the extensive deployment of AI/ML models on medical devices with limited resources, such as implantable devices, wearable devices and point-of-care devices. TDC'22 is only the starting point for TinyML in healthcare. TinyML could result in the creation of new and innovative solutions such as cross-layer codesign[8–10] to healthcare problems, allowing continuous and personalized care to be provided to patients with minimal expertise and cost.

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