End-to-end evolutionary neural architecture search for microcontroller units

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Abstract
Smart wearable devices require accurate, fast, and energy-efficient neural networks to allow for optimal application performance. To advance the field of neural architecture search (NAS), we introduce our end-to-end evolutionary NAS (EvonAS) for microcontroller units that optimize both pre-processing and network architectures. Each neural network architecture is assessed using the multi-objective accuracy, memory footprint, inference time, and energy consumption, to derive a common performance measure to be maximized. To ensure immediate use of all potential solutions on the microcontroller environment, we create a software/hardware chain in which each neural network is deployed to measure the inference time and power consumption directly. In a proof-of-concept study, we focused on the analysis of audio-based speech commands. Our experiments suggest that 2D convolutional layers with automatically set pre-processing (short-time Fourier transforms) outperform 1D convolutional layers with raw audio signals. We show that our end-to-end EvonAS scales with the complexity of the classification task and is still able to find constraint-preserving, and thus deployable, Pareto-optimal neural network architectures even when the classification task is more complex. Our proposed EvonAS approach is dataset and hardware-agnostic, allowing a universal use across a wide range of applications.

Introduction
In this work, we propose an end-to-end software/hardware chain based on an evolutionary neural architecture search (EvonAS) to optimize 1D and 2D preprocessing and neural network architectures in a single step. Found combinations are contained in a single model file and directly tested on the target hardware allowing for immediate use in a production environment. In our proof-of-concept study we utilized the Speech Commands dataset (see Figure 1).

Main contributions:
- We propose a fully functional, scalable software-hardware end-to-end pipeline for evolutionary NAS.
- We included 2D audio preprocessing (short-term Fourier transform) as part of the evolutionary optimization. This enables direct deployment and allows for end-to-end design.
- We found that 2D convolutional neural networks outperform 1D networks in terms of overall fitness achieved.
- We show that our optimization algorithm is able to find Pareto-optimal architectures.

Methods
Hardware/software setup:
- IRFS2840 (32-bit ARM Cortex-M4) Development Kit Board from Nordic Semiconductor
- Power Profiler Kit (PPK) from Nordic Semiconductor
- Zephyr RTOS
- TensorFlow and TensorFlow Lite Micro
- Kappe Python library

To find neural network architectures we utilized evolutionary optimization as shown in Figure 2.

Each of the sampled preprocessing and neural network architecture combinations (see Figure 3A) is evaluated against a common multi-objective function to determine its fitness. We combine four constrained target measures as a weighted sum into a fitness function that penalizes models that violate constraints and favors models that are better than the given constraint. The fitness function F is described by the following equation:

\[ F = \alpha A + \beta B + M \max - y + T \max + W \max \]

where A is the accuracy of the validation dataset, M the obtained memory footprint in Bytes (B), T the measured inference time (see Figure 3B) in Milliseconds (ms), and W the energy consumption in Millijoule (mJ).

Results
Computations in 2D space outperform 1D neural networks

Regardless of the gene pool, our algorithm is able to converge to a maximum fitness value with our given hyperparameter set (see Figure 4). Using 1D instead of 2D convolutional layers leads to lower fitness values. All of the best optimized models satisfy previously defined constraints regarding inference time, memory footprint and energy consumption (\( M_{\text{max}} = 0.8 \text{ MB} \), \( T_{\text{max}} = 200 \text{ ms} \), \( W_{\text{max}} = 2 \text{ mJ} \)).

EvonAS yields Pareto-optimal neural architectures

Our end-to-end EvonAS is able to find Pareto-optimal neural architectures (see Figure 5). If a given neural architecture has a memory footprint less than 158B and an energy consumption per increasing less than 1.8mJ, the accuracy drops drastically. Increasing both objective measures leads vice versa to higher classification accuracies. Restricting ourselves to neural architectures that performed best on a given objective measurement (Figure 6), we observe architectures that perform very well in terms of energy consumption, while others have high performance in terms of accuracy. However, our algorithm finds a variety of Pareto-optimal neural networks driven by the predefined fitness function \( F \).

Considering the model with the best Fitness, assuming we use a 200mAh battery and execute our EvonAS architecture twice per second (i.e. a 2 Hz rate), we can run our deployed network continuously for 89.8h without the need for a recharge (on average \( T_{\text{max}} = 2 \text{ mJ} \), \( W_{\text{max}} = 4.5 \text{ mJ} \)).

Discussion
We are able to find neural networks that don’t violate any of the given constraints and that are directly deployable on the hardware they were optimized for. However, especially the test accuracy of the 12-classes Speech Commands classification task is highly affected compared to other state-of-the-art networks. This could be due to the downsampling step we performed, as the SRAM peak memory consumption of the neural network would be too high when used in the microcontroller. Additionally, the used implementation of the TFLM-compatible STFT layer in the kappe python library leads to too large memory footprints if parameters are outside of a very confined range, e.g. \( n, f_t \).

In future work, we also plan to include Mel spectrogram/MFC preprocessing instead of only STFT in our gene pool. We will also increase the search space of EvonAS by expanding the gene pool to find more complex, elaborate neural network architectures.

References

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