Supplementary Information Guide

TABLE OF CONTENTS

SUPPLEMENTARY NOTES' TITLES

Supplementary Note 1. Proposed application of the Microwave Neural Network in a wideband receiver chain

Supplementary Note 2. Proposed readout for compressed spectral features without a spectrum analyzer

Supplementary Note 3. Comparison of predicted accuracy with and without the Microwave Neural Network

SUPPLEMENTARY FIGURES' CAPTIONS

Fig S1. A single receiver can be used to produce a baseband signal that frequency-modulates a square wave that is fed to the MNN. Its feature-rich output could be used by a cheap backend neural network, for inference (instead of a power-hungry Graphics Processing Unit).

Fig S2. The integration of a low-bandwidth receiver on-chip involves using 4-phase passive mixers to down-convert the outputs of the coupled oscillators to low-frequency baseband signals (<50 MHz). These signals should contain compressed features from the MNN's computations on high-bandwidth data and can replace the off-chip spectrum analyzer previously used for readout. The remainder of the integrated circuit consisting of coupled oscillators, couplers and gain remains the same.

Fig S3. Comparison of MNN-assisted and backend-neural-network-only accuracy. (a) Bit sequence search accuracy at 10 Gbit/sec for various queried bitstream lengths. The MNN (blue) consistently achieves higher accuracy than the optimized linear layer (orange) across all queried bitstream lengths. (b) Using the MNN enhances the accuracy of counting the number of flying targets, particularly in complex cases with 3 to 6 aircraft, where the backend neural network struggles to resolve ambiguity.

SUPPLEMENTARY TABLE'S TITLE

Supplementary Table 1. Comparison of the accuracy and complexity of state-of-the-art digital neural networks and the MNN for the standard task of wireless signal encoding classification using the RadioML2016 dataset.

SUPPLEMENTARY INFORMATION REFERENCES

S1. Yi, X., Wang, C., Chen, X., Wang, J., Grajal, J., & Han, R. (2021). "A 220-to-320-GHz FMCW Radar in 65-nm CMOS Using a Frequency-Comb Architecture." *IEEE Journal of Solid-State Circuits*, 56(2), 327–339. https://doi.org/10.1109/JSSC.2020.3020291

S2. J. Al-Eryani et al. "Fully Integrated Single-Chip 305–375-GHz Transceiver With On-Chip Antennas in SiGe BiCMOS". In: IEEE Transactions on Terahertz Science and Technology 8.3 (May 2018), pp. 329–339. doi: 10.1109/TTHZ.2018.2823202.

S3. A. Ghaffari, E. A. M. Klumperink, M. C. M. Soer and B. Nauta, "Tunable High-Q N-Path Band-Pass Filters: Modeling and Verification", *Solid-State Circuits IEEE Journal of*, vol. 46, pp. 998-1010, 2011.

S4. O'Shea, Timothy J., Corgan, Johnathan, and Clancy, T. Charles. "Convolutional Radio Modulation Recognition Networks." *arXiv preprint arXiv:1602.04105*, 2016.

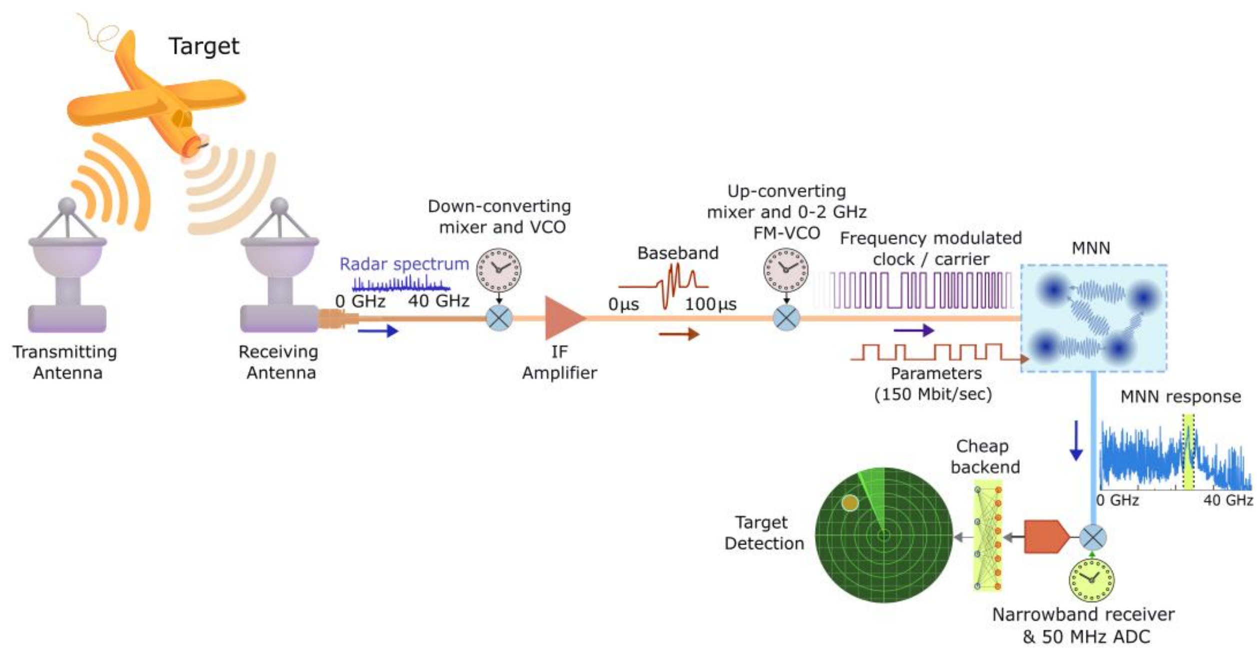
S5. Courtat, Thomas, and Hélion du Mas des Bourboux. "A light neural network for modulation detection under impairments." *arXiv preprint arXiv:2003.12260*, 2020.

S6. Ramjee, Sharan, Ju, Shengtai, Yang, Diyu, Liu, Xiaoyu, El Gamal, Aly, and Eldar, Yonina C. "Fast Deep Learning for Automatic Modulation Classification." *arXiv preprint arXiv:1901.05850*, 2019.

1. Proposed application of the Microwave Neural Network in a wideband receiver chain

In radar systems, microwave signals are transmitted to a target, and the reflected signals are captured by receiving antennas. Supplementary Ref [1] highlights that a wideband receiver using parallelized signal chains that process smaller frequency bands (e.g., 0-2 GHz, 2-4 GHz, ..., 18-20 GHz) can provide consistent Effective Isotropic Radiation Efficiency (EIRP) and Noise Figure across the full spectrum. Each signal chain consists of dedicated mixers, voltage-controlled oscillators (VCOs) filters, with each Intermediate Frequency (IF) signals digitized by an Analog-to-Digital Converter. They would be sent to a GPU for target detection. However, this approach is power-intensive and the receiver does not add learned features that could ease machine-learning inference for environments with multiple dynamic targets.

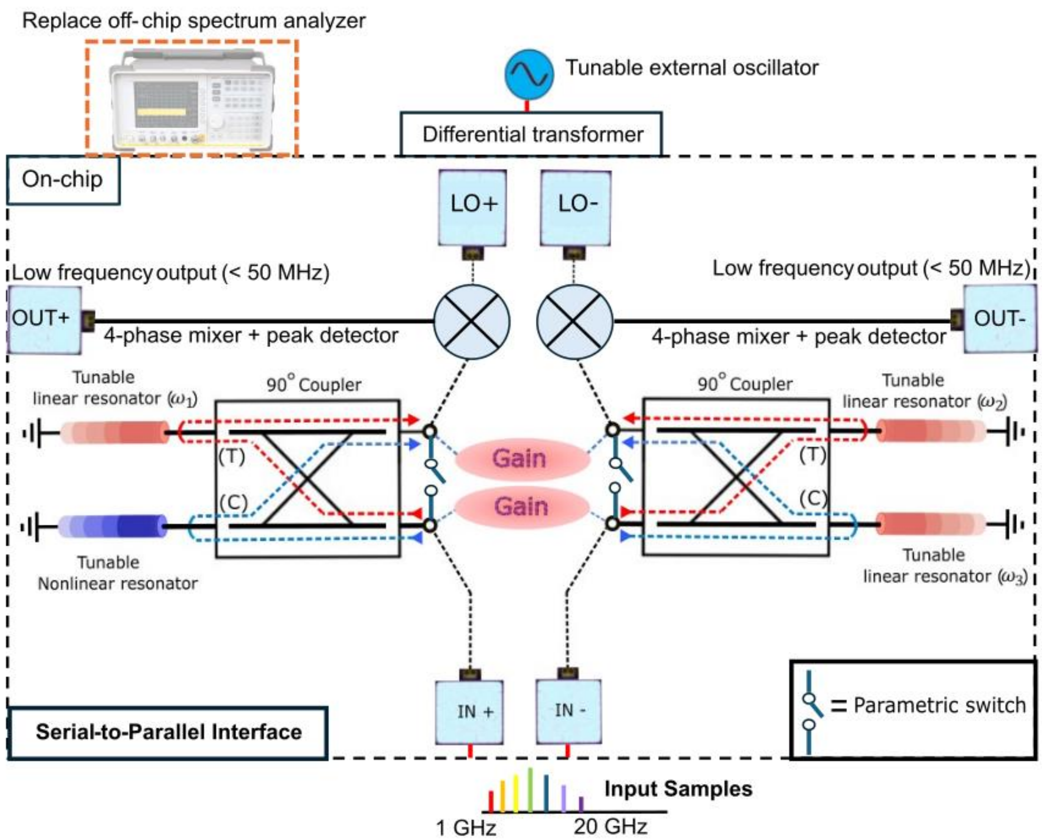
The Microwave Neural Network (MNN) presents a simpler alternative. It can be integrated within a single receiver, such as that in Supplementary Ref [2]. Supplementary Fig. 1 shows its proposed position within the signal chain. The MNN, owing to its extreme sensitivity to input signals, adds learned features through its nonlinear expansion functions, even when paired with a suboptimal radar front-end. As explained in Fig. 4a.i of the main article, the baseband signal frequency-modulates a carrier (FM-VCO), and slow parameter bits (150 MBit/sec) enable the MNN to perform computation. A single down-conversion mixer (see Supplementary Note 2) and sub-50 MHz ADC can then manage readout. A lightweight neural network then maps compressed features to target trajectories without the need for power-hungry GPUs.



Supplementary Fig 1. A single receiver can be used to produce a baseband signal that frequency-modulates a square wave that is fed to the MNN. Its feature-rich output could be used by a cheap backend neural network, for inference (instead of a power-hungry Graphics Processing Unit).

2. Proposed readout for compressed spectral features without a spectrum analyzer.

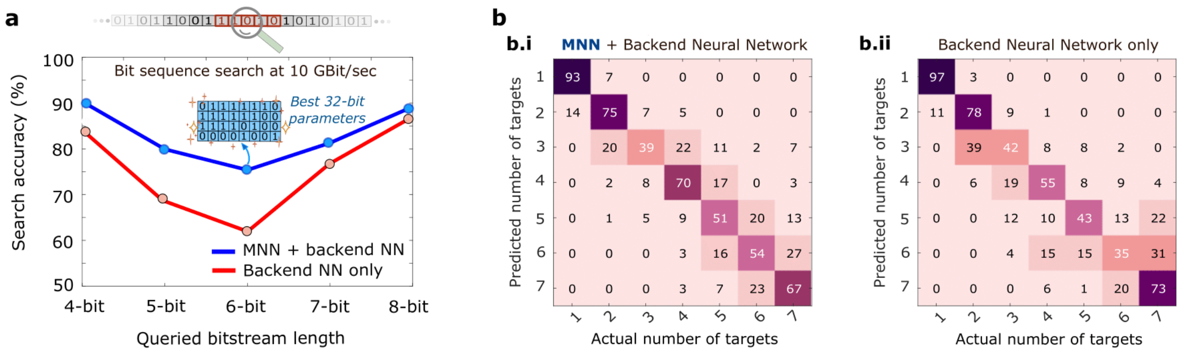
The Microwave Neural Network presented in the main article utilized off-chip digitization with a spectrum analyzer that read off a narrow band of frequencies. In a fully integrated version we have fabricated (not discussed in the main article), we have proposed replacing this with an on-chip solution, whose schematic is shown in Supplementary Fig. 2. Here, incoming microwave drive signals interact with the MNN's parametric oscillations to produce distinct comb-like spectra. Instead of feeding directly to the output pads, processed signals from the couplers' outputs are directed to two mixers that down-convert portions of these spectra based on the frequency of a tunable external differential oscillator. This employs an 'N-path' topology (Supplementary Ref [3]), functioning as a tunable bandpass filter at RF frequencies, translating signals in that band to differential, sub-50 MHz outputs. The quality factor of these filters determines the bandwidth of the received baseband signal. This signal can then be digitized with a low-bandwidth, sub-50 MHz analog-to-digital converter, either on- or off-chip, and the features used to train a linear backend neural network. For even simpler readout, on-chip peak detectors can instead be used to record the power at the desired frequency.



Supplementary Fig. 2. The integration of a low-bandwidth receiver on-chip involves using 4-phase passive mixers to down-convert the outputs of the coupled oscillators to low-frequency baseband signals (<50 MHz). These signals should contain compressed features from the MNN's computations on high-bandwidth data and can replace the off-chip spectrum analyzer previously used for readout. The remainder of the integrated circuit consisting of coupled oscillators, couplers and gain remains the same.

3. Comparison of predicted accuracy with and without the Microwave Neural Network

Supplementary Fig. 3 compares performance with and without the MNN in the path of incoming signals. Results with the MNN present are repeated from the main article. For the bit-sequence detection task, for the case of without using MNN, the linear layer is directly trained with on time-domain sequences. For the radar tracking task, the frequency modulated square waves (as in the main article) are fed directly to the spectrum analyzer, and the output spectra are truncated to the reduced frequency ranges used by the MNN. The backend neural networks discussed in Methods Section 5 are reused here for fair comparison. In the representative results shown below, for both digital emulation and RF communication, tasks, the inclusion of the MNN improves accuracy. For bit sequence detection, the MNN achieves higher search accuracy than the optimized linear-layer backend across all queried bit-sequence lengths, exceeding it by 10% in the worst case of 6-bit queries. When analyzing flight patterns in simulated airspace, the MNN shows a clear improvement in accurately predicting the number of flying targets, especially in the worst cases with 3 to 6 aircraft.



Supplementary Fig. 3.: Comparison of MNN-assisted and backend-neural-network-only accuracy. **(a)** Bit sequence search accuracy at 10 Gbit/sec for various queried bitstream lengths. The MNN (blue) consistently achieves higher accuracy than the optimized linear layer (orange) across all queried bitstream lengths. **(b)** Using the MNN enhances the accuracy of counting the number of flying targets, particularly in complex cases with 3 to 6 aircraft, where the backend neural network struggles to resolve ambiguity.

Supplementary Table 1. Comparison of the accuracy and complexity of state-of-the-art digital neural networks and the MNN for the standard task of wireless signal encoding classification using the RadioML2016 dataset.

Model	RadioML2016.10a Val. Accuracy at 18dB SNR	Number of Parameters
RML-ResNet [S4]	90%	240K
Mod-LRCNN [S5]	91%	100K
CLDNN [S6]	88%	6.5M
MNN + Lin. Backend (ours)	87.4%	<7K (linear layer) + 32 bits