Deep Learning for Real-time Classification of Astronomical Radio Signals

Evaluating the Applicability of Synthetic Data for Training

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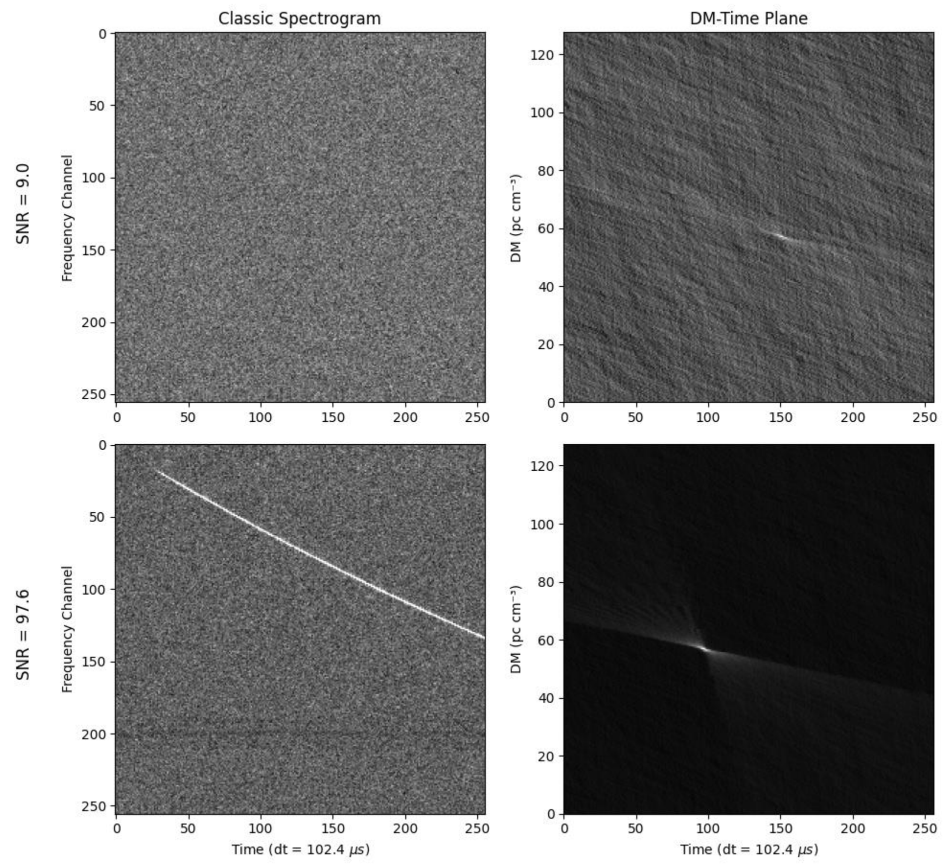
Astronomical Radio Signals

In this work, astronomical radio signals are understood as signals from two types of cosmic sources of pulsed radio emission: pulsars and fast radio bursts (FRBs).

Pulsars are rapidly rotating neutron stars with extremely strong magnetic fields. The unique conditions in their magnetospheres (Philippov & Kramer, 2022), as well as in their interiors (Lattimer & Prakash, 2001), make them key objects for fundamental physics. In addition, pulsars have broad astronomical importance: they are used in the search for gravitational waves (EPTA Collaboration, 2024), in the study of the interstellar medium (Woods, 2024), and in tests of general relativity (Freire & Wex, 2024).

Fast radio bursts, in contrast to pulsars, are not stable sources of emission but rather a phenomenon manifesting as extremely powerful extragalactic radio pulses of very short duration. Their nature remains not fully understood to this day (Petroff et al., 2022).

The main characteristic of astronomical radio signals



One of the key properties of astronomical radio signals is the dispersion measure (DM). It is defined as the integrated column density of free electrons along the line of sight and is a fundamental quantity that confirms the cosmic origin of the emission. The dispersion measure causes a frequency-dependent delay of the signal, expressed as

$$\Delta t = 4.15\,[ms] \times \left[f_l^{-2}[GHz] - f_h^{-2}[GHz]\right] \times DM[cm^{-3}pc],$$

where Δt – the time delay between f_l and fh, f_l – the low frequency, f_h – the high frequency, DM – the dispersion measure.

In practice, registered pulses from pulsars or fast radio bursts are usually very weak and often hidden in the noise. To increase signal to noise ratio (SNR), a process known as dedispersion (Hankins & Rickett, 1975) is applied: the frequency-dependent delays are compensated according to the dispersion measure, which improves the signal fidelity.

For signals in which we do not know the DM a priori e.g., in the case of new FRBs, an effective way to detect the signal is to compute several DM dedispersion trials, the result of which is the DM-time data. In such representation the true DM of the astronomical source appears as a sharp, localized feature that separates the signal from terrestrial interference, and providing a structured representation that can serve as an effective input for machine learning and deep learning models aimed at pulse detection or classification.

Minimalistic Models for Pulsar and FRB Detection

Astrophysicists are actively applying modern machine learning and deep learning methods to the detection and study of pulsars and FRBs. However, a review of the literature shows that such tasks are often addressed using rather complex and deep neural networks (see, e.g., Agarwal et al., 2020), which were originally developed for ILSVRC and other computer vision competitions. These models indeed demonstrate impressive performance in the classification and detection of astronomical radio signals. Nevertheless, it is important to note that such signals exhibit significantly lower complexity compared to images in ImageNet. This mismatch raises the question of whether the use of extremely deep and computationally heavy architectures is fully justified in this domain.

Given the relatively low complexity of the data, it can be assumed that the task of pulse detection can be successfully solved with models containing far fewer parameters. Minimalist architectures offer a number of advantages over deep networks: smaller model size, substantially faster inference speed, and generally easier to train, require fewer computational resources, and can be more readily adapted to real-time applications. In addition, lightweight models can be easily implemented on Field Programmable Gate Arrays (FPGAs).

In this work, we tested a group of four extremely compact models and evaluated their ability to successfully detect individual pulses from the Crab pulsar (B0531+21), using observational data obtained with the Effelsberg radio telescope operated by the Max Planck Institute for Radio Astronomy. A key feature of these architectures is the use of a Global Average Pooling layer, which makes it possible to drastically reduce the number of parameters without a significant loss in performance.

Applicability of Synthetic Data

In addition to minimalist models, this study explored training solely on synthetic data with subsequent testing on real observations. Given the current comprehensive understanding of pulsar emission mechanisms and the factors determining the observable pulse morphology, it is now possible to construct highly realistic synthetic datasets, which were therefore employed for training.

Obtaining large labeled datasets is often difficult, especially for rare events such as FRBs, so synthetic data provide a practical solution. Pulses were generated with the PulsarRFI_Gen submodule of the ML-PPA framework (gitlab.com/ml-ppa), capable of producing realistic dispersed signals.

Noise was modeled in two ways: (1) random shifting of frequency channels (*real mode*), and (2) generation from statistical parameters of real data (*synt mode*). Each dataset contained 94,000 synthetic pulses of the Crab pulsar (1,000 per SNR from 6 to 100), 47,000 broadband interference samples, and 47,000 noise-only DM–time images.

In total, four datasets were produced: two for training and two *unseen* for validation. Final tests used real observations of the Crab pulsar (B0531+21) from the Effelsberg radio telescope of the Max Planck Institute for Radio Astronomy. Model performance was evaluated with the F1-score.

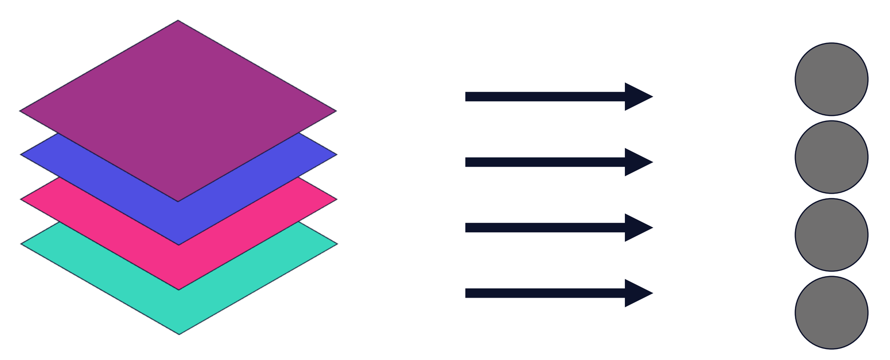
$$F1 = \frac{2 \times Precision \times Recall}{Precission + Recall}$$

1. MJD 58713, t_{res} = 64.0 μs, BW: 1330 - 1460 MHz
2. MJD 59000, t_{res} = 102.4 μs, BW: 1210 - 1530 MHz
3. MJD 59000_2, t_{res} = 64.0 μs, BW: 1210 - 1530 MHz
4. MJD 60482, t_{res} = 81.92 μs, BW: 1200 - 1600 MHz

Model name	Mode	Size (KB)	Parameters	Accuracy (%)	$F1_{real}$ (%)	$F1_{synt}$ (%)	$F1_1$ (%)	$F1_2$ (%)	$F1_3$ (%)	$F1_4$ (%)	$F1_{aver}$ (%)
LeNet5 + GAP	real	143	8 471	99.99	99.97	99.98	99.19	98.33	93.09	90.08	96.77
	synt	105	5 134	99.99	99.02	98.98	88.66	86.75	64.66	73.09	85.19
MobileNet V1 Trim	real	96	658	99.97	99.89	99.89	98.77	97.53	89.66	85.29	95.17
	synt	96	584	99.98	33.33	33.33	32.38	32.19	31.85	29.53	32.10
Mini-SqueezeNet	real	99	1 424	99.98	98.76	98.79	93.98	81.77	62.83	70.87	84.50
	synt	103	1 960	99.96	99.92	99.93	93.06	92.68	89.22	84.80	93.27
Shallow CNN	real	78	2 942	99.99	99.90	99.90	97.64	96.30	85.46	87.31	94.42
	synt	87	3 666	99.98	99.87	99.87	95.63	97.07	92.52	90.22	95.86

Global Average Pooling (GAP) Layer

It is a neural network layer often used in convolutional architectures to reduce dimensions efficiently:
It computes the average value of each feature map, replacing spatial dimensions with a single number. This avoids overfitting, decreases parameter count, and improves generalization.
Unlike fully connected layers, it has no learnable weights, making the model simpler and faster while preserving semantic information.



Conclusion

The evaluation of four lightweight models on both synthetic and real data from the Crab pulsar (B0531+21) confirmed their effectiveness. The models achieved average F1-scores above 90%, with peak values exceeding 96%, showing that high detection accuracy does not require large, computationally expensive networks. Even under reduced signal-to-noise ratios and in the presence of synthetic noise, the models demonstrated stable generalization.

These results highlight the potential of combining synthetic datasets with compact architectures as a practical strategy for pulsar and FRB detection. Such an approach simplifies implementation, reduces computational demands, and opens opportunities for efficient real-time processing in large-scale radio astronomy projects.

Partner institutions:

technische universität dortmund
Fraunhofer IAIS
UNIVERSITÄT BONN
Fraunhofer IML

Institutionally funded by:

Bundesministerium für Forschung, Technologie und Raumfahrt
Ministerium für Kultur und Wissenschaft des Landes Nordrhein-Westfalen