Automated morphological classification of Fast Radio Bursts using the Deep Learning framework

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Fast Radio Bursts (FRBs) show a wide variety of temporal and frequency structures in their dynamic spectra that could indicate different origins or emission mechanisms. CHIME and other radio telescopes have detected a large number of FRBs and the detection rate is expected to increase in the future. While the morphology of FRBs is very diverse, it is not clear whether different FRBs emerge from different emission mechanisms/astrophysical channels. Rapid, automated classification of FRB morphologies will aid multiwavelength follow-up (e.g. with ground- and space-based telescopes) by the prioritisation of rare and anomalous events. We are developing a training set generator and a convolutional neural network (CNN) based Deep Learning framework classifier that can identify FRB morphology, detect anomalies, and help quantify statistics of FRB morphologies. FRB morphology statistics can help constrain various emission mechanism models for the FRB. We have simulated datasets for training in the form of images (intensity as a function of time and frequency) based on various observed FRB morphologies and extending their parameter spaces. We simulate bursts for each type while varying different burst parameters like fluence, width, scattering measure, spectral index, number of components etc. for signal to noise ratio (SNR) values of 15, 25, 35, 50, and 100 for each of the five broad categories we identified. These five categories include single-component FRBs with broad or narrowband spectra, multicomponent FRBs, and the downward drifting substructures (‘sad trombone’) often seen in repeaters. For low SNRs, large scattering or temporally wide components, multiple components can merge into one and may be challenging to distinguish by eye. Deep Learning Models are proven to be very effective in picking out specific patterns in images. We have trained and optimized the deep learning models on the simulated training set of input dynamic spectra. We will discuss our methodology and the results on the classification. The code and example data for the framework will be made available for community usage.