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YOLO for Radio Frequency Signal Classification

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***Abstract*—Radio frequency signal classification plays a pivotal role in various applications, including spectrum management, wireless security, and cognitive radio. Extant signal classification methods require significant data throughput and are not multilabel. We propose a novel approach to radio frequency signal classification by leveraging the You Only Look Once (YOLO) object detection method. YOLO is a state-of-the-art deep learning model renowned for its real-time object detection capabilities in computer vision applications. We adapt YOLO for signal classification to enable the automatic and efficient identification of various signal types within a power spectral density image.**

***Index Terms*—radio-frequency analysis, object detection, neural networks, machine learning, deep learning**

I. Introduction

Identifying signals of interest in a given radio-frequency (RF) band has applications in signal intelligence, spectrum management, and cybersecurity. Continuous spectrum monitoring necessitates the sensing and identification of signals of interest. We propose a method that uses deep learning (DL) to identify and frame various signals that are present in an environment. This DL framework is based on the *You Only Look Once* (YOLO) object detection pipeline [1]. Our work demonstrates a specific application of computer vision to the field of telecommunications.

A. Review of existing methods

Within a defined bandwidth, we seek to identify predetermined signals of interest in near-real-time. Existing efforts (see e.g. [2]–[4]) for radio-frequency (RF) signal classification focus on whole image classification and are multi-class, not multi-label, machine learning approaches. These works rely on favorable signal-to-noise-ratio in samples. A related approach to signal classification is device identification. The findings of works such as [5] and [6] describe device identification within a specific protocol and do not identify a generalized set of protocols within a band. Our approach allows for specific signal identification via bounding boxes. Moreover, our solution can handle the presence of arbitrarily many classes within an image. Both [7] and [8] apply YOLO to signal detection. In [7], a method based on YOLOv1 is applied in a single-label setting and does not employ anchor boxes. Our work used YOLOv7 [9] (with anchor boxes) and is multi-label. Soltani et al. [8] use YOLOv3, but rely on a two-pass system of coarse and fine signal detection to appropriately locate signals of interest.

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B. Data typology

Each of the methods outlined in [2]–[6] rely on raw in-phase and quadrature phase (I/Q) signal data. However, this data typology presents several challenges. At typical sampling rates, I/Q values produce such a considerable amount of data that it is unfeasible to handle the raw data without downsampling and filtering the data. This downsampling process dilutes the descriptive benefit of using I/Q values. Furthermore, I/Q values are much less human interpretable and do not allow for direct localization of specific protocols of interest. Unlike raw I/Q value data, power-spectral-density (PSD) spectograms can provide a simpler, human interpretable, visualization of signals within a given band. In practice, the PSD is estimated by periodograms, which are the squared components of the associated fast Fourier transform of the signal. A series of intensity-encoded estimated PSD spectograms may be stacked over time to create a waterfall plot (see Figure 1). Using these waterfall plots, the areas of the image associated with signals of interest can be labelled using bounding boxes. These bounding-box-labelled images are used as input to the YOLO model, as described in Section III.

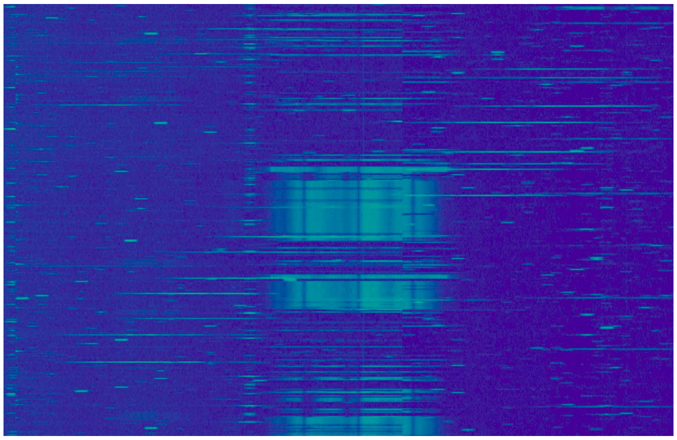

Fig. 1. Estimated PSD intensity waterfall plot

II. Computational Tools

Data collection was conducted using a Signal Hound SM200C connected to a Dell Precision 7770 laptop. The WiFIRE software from Idaho National Laboratory (INL) [10] was used for signal visualization and analysis; model training was performed using the Hoodoo cluster on INL's High Performance Computing (HPC) Center; data labeling was done via Yolo Mark.

III. You only look once

The YOLO method is an established DL framework for object detection in images [1]. Many examples of YOLO being applied to standard photograph-like images exist. Unlike traditional object detection, however, we must detect signals which can be of ambiguous form and are subject to distortion from unfavorable SNR. We collected 3,805 total PSD waterfall images containing three common RF signal protocols used in the railroad industry: narrow-band FM (NBFM), positive train control (PTC), and head-of-train/end-of-train device (HTD/ETD) telemetry. These signal types were chosen to satisfy customer needs; however, preliminary work in the 300-400MHz (various automobile key fobs), 900 MHz, and 2.4 GHz bands indicate our method easily generalizes.

Collected images were labeled with bounding boxes around each instance of the protocols in question. We fit three models of tiny-YOLOv7 (one for each protocol set). Model hyperparameters were the same for each instance: `batch size`: 32; `epochs`: 1000; `optimizer`: Adam. Model training loss was as detailed in [9]. Average training time was 3.46 hours. The precision and recall for a withheld test set of images was recorded to obtain an F_1 score for each model. Data and relevant code are located on the INL HPC GitLab site at https://hpcgitlab.hpcondemand.inl.gov. Please coordinate with the authors for further guidance.

IV. Results

We fit models for the three protocols given in Section III. The results of these models are presented and discussed below.

A. Presentation of results

Figure 2 depicts a sample of the results for each protocol examined. Each sample image was taken as a grayscale image. The test inference threshold was set to 0.3. The associated bounding boxes and the confidence scores are marked accordingly. The respective F_1 scores of the NBFM, PTC, and HTD/ETD models are 0.938, 0.906, and 0.861.

B. Discussion of results

Under the premise of identifying specific signals of interest, each model performs sufficiently well overall. The stated F_1 scores are indeed higher than is normal for YOLO in general. The simplicity of the signal presentations (vertical lines with consistent horizontal location in every image) aids in this regard. Improvements to the model could be achieved by adjusting the predefined anchor boxes to have thinner width. This would allow us to better capture the typically long and thin signal shapes for these protocols. Furthermore, image data that is RGB instead of gray scale could allow for full use of the input channels of the YOLO convolutional structure.

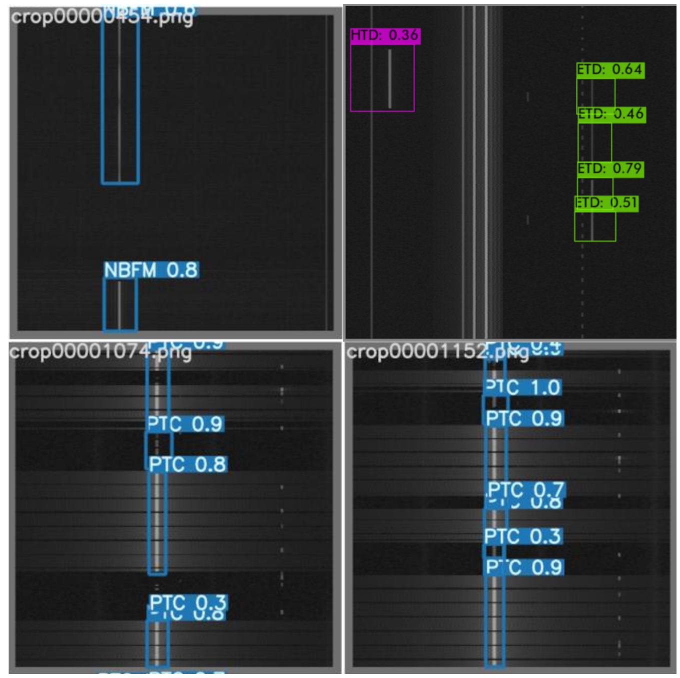

Fig. 2. Images with predicted signals labeled by YOLO. Beginning in the top left and moving clockwise: NBFM, HTD/ETD, PTC, PTC

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