Speclearn: Spectrum Learning in Shared Band under Extreme Noise Conditions

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***Abstract*—This paper focuses on the detection of radar signals within the shared spectrum, such as the Citizen Broadband Radio Service band, employing machine learning methodologies. The study investigates the influence of various types of synthetic noise on the spectrum, thereby affecting the accuracy of signal detection in shared regions. Our approach involves the utilization of a YOLOv5-based object detection method, where a trained model is generated using clean spectrograms as input. The trained model is then evaluated for their detection performance under diverse noise conditions. The analysis reveals that an extremely noisy environment leads to a detection failure of 0%, while low noise conditions remain tolerable without any noticeable performance degradation. This study provides valuable insights into the robustness of machine learning-based radar signal detection in real-world, noisy scenarios within shared spectrum environments.**

I. Introduction

Necessity of spectrum learning in shared band. The 3.5 GHz Citizen Broadband Radio Service (CBRS) band has recently been opened by the Federal Communication Commission to secondary users, including cellular service providers, private networks, and IoT applications on conditional access by safeguarding primary users' (naval radar) activities [1]. To detect the radar activity in this band, the Spectrum Access System (SAS) communicates regularly with Environmental Sensing Capability (ESC) stations near coastal regions, with ESC certification requiring 99% accuracy and detection of radar pulse bursts within 5 seconds [2]. Achieving this constraint is difficult due to the various noises received at the ESC along with present signals which can decrease the accuracy of radar signal detection. Consequently, this challenge has sparked considerable interest within the research community, prompting investigations into the prospect of leveraging machine learning methods based on object detection. The goal is to learn the spectrum effectively, enabling the earlier detection of radar activity compared to traditional methods.

State-of-the-art for radar detection using spectrum learning. In that direction, the state of the art (Waldo [3], DeepRadar [2] and RadYoloLet [4]) use the variation of the widely used object detection based machine learning algorithm You Only Look Once (YOLO) to detect radar signals in the CBRS band from spectrograms generated at the ESC sensor. All these approaches consider the interference in the CBRS band in terms of 5G and LTE signals.

Consideration of added noise at the ESC sensors. The current studies have not experimented with the possibility of the spectrogram images getting degraded with different noise conditions at the ESC sensors. The noise can be in the form of Gaussian noise generated at the radio receiver in the ESC sensors [5]. Additionally, noise can manifest in the generated spectrogram images from the received signals at the ESCs. These distortions in the images occur due to the interference in the transmission channel in the form of Speckle and Salt&Pepper noise [6].

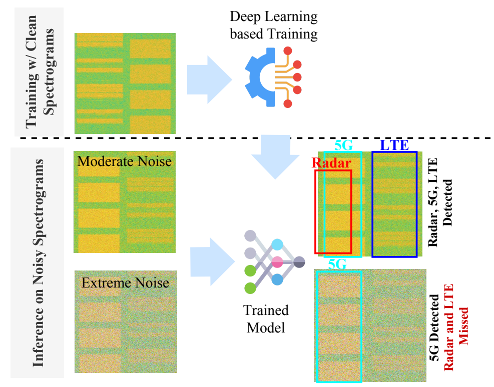


Fig. 1. The pipeline for Speclearn framework.

Speclearn framework. In Speclearn, we consider various unforeseen noisy conditions during the inference or deployment time. As shown in Fig. 1, we train a deep learning based model on the clean spectrograms and expose the trained model to different noisy conditions. Our contributions are:

(C1) Creation of a robust pipeline for radar detection based on spectrogram analysis in challenging, noisy environments. The proposed approach involves training a single-stage YOLO-based machine learning model on clean spectrograms.

(C2) Introduction of various synthetic noise conditions to emulate the complex and noisy conditions at the ESC sensors.

(C3) Execution of a comprehensive experimental analysis of the proposed approach on publicly available dataset of synthetic spectrograms in the CBRS band.

II. Experiments

A. *Speclearn Framework*

The conceptual overview of our proposed framework is illustrated in Fig. 1. We design the framework to examine scenarios where arbitrary noises could potentially impact the system. Our experimentation involves the introduction of three types of widely explored synthetic noises: Gaussian, Speckle, and Salt&Pepper noises. For each of these noise types, we establish three distinct levels—low, medium, and high by varying the variance. Employing a single-stage YOLOv5 model

Table I: Performance of training the YOLOv5 model on clean spectrograms.

Metric	Signal Type		
	Radar	5G	LTE
Recall	0.943	0.985	1
Precision	0.947	0.991	0.981
Mean Average Precision	0.986	0.984	0.99

trained on *clean* or no-noise signals, we train our model and assess its robustness by subjecting it to various synthetic noisy conditions during testing.

Highlight: It is to be noted that we use a single-stage YOLOv5-based solution unlike different complex models and execution pipelines used in the state-of-the-art [2], [3], [4].

B. Experimental Setup

Dataset: We evaluate our proposed framework by using the synthetically generated *clean* spectrograms from [7]. The dataset contains $\sim$ 1000 `MATLAB` generated spectrograms of 10 MHz spectrum for $20ms$ with $\sim$ $30dB$ signal to noise ratio (SNR), emulating a coastal region with 5 ESC sensors along the coast with one LTE and one 5G base station (details in [7]). Each spectrogram has either: (a) Radar and LTE, (b) Radar and 5G, or (c) Radar, LTE, and 5G signals.

Training: We train the YOLOv5 architecture on 80% (validated on 5%) of the dataset from [7] using *stochastic gradient descent* optimizer with batch size of 16 for 100 epochs.

Inference: We use the rest of the 15% of spectrograms for inference. We also generate nine set of noisy versions of those spectrograms following different noise levels for Gaussian, Salt&Pepper, and Speckle noises, presented in Table II. A snapshot of various generated noises is shown in Fig. 2.

Performance metrics: We use the standard performance metrics such as recall, precision and mean average precision for evaluating the training. During inference, we calculate the detection accuracy as the true positives detected by the model divided by the total true positives.

C. Experimental Analysis

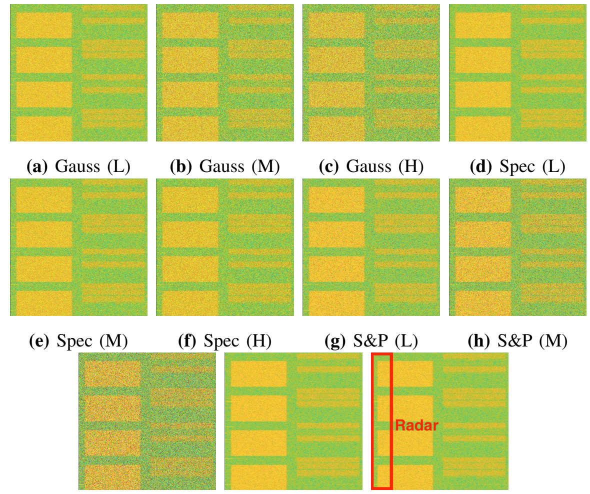
We train the model on the clean spectrograms and use the trained model to obtain detection accuracy of different signal types in the noisy spectrograms during inference phase. The training performance is presented in Table I while the results of the inference phase are summarized in Table II. The inference time for one spectrogram in `google colab` is $11ms$.

• **Observation:** We observe that the trained model detects radar signals with 100% accuracy on clean spectrograms. The radar detection performance degrades significantly with high noisy conditions for all types of noises, which is not the case for LTE and 5G detection, as radar pulses are harder to detect [3] and easier to miss compared to the more prominent LTE and 5G signals. These numbers may change with a higher detection threshold during inference, subjected to future work.

• **Future Direction:** We will employ sophisticated machine learning-based training mechanism such as meta and transfer learning techniques for improving robustness of Speclearn in high noise conditions.

III. Conclusions

This paper presents a YOLOv5-based pipeline for radar signal detection in shared spectrum scenarios. The pipeline is trained on clean spectrograms and evaluated in noisy



(a) Gauss (L) **(b)** Gauss (M) **(c)** Gauss (H) **(d)** Spec (L) **(e)** Spec (M) **(f)** Spec (H) **(g)** S&P (L) **(h)** S&P (M) **(i)** S&P (H) **(j)** No-noise **(k)** No-noise

Fig. 2. Spectrograms under different noise conditions: (a) - (i) show different levels of noises in all three types of simulated noises on the clean spectrogram (j). The (k) shows the bounded radar signal in (j).

Table II: The detection performance. The radar signal detection performance decreases significantly with more noise, unlike LTE and 5G signal detection.

Noise Type	Noise Variance	Detection Acc. (%)		
		Radar	5G	LTE
None	-	100	100	100
Gaussian	Low (0.012)	98.1	98.6	100
	Mid (0.05)	51.85	94.5	97.43
	High (0.075)	21.3	90.4	98.7
Salt&Pepper	Low (0.05)	97.2	98.6	100
	Mid (0.12)	78.7	97.3	98.7
	High (0.25)	8.33	100	100
Speckle	Low (0.012)	99.1	98.6	100
	Mid (0.025)	96.3	98.6	98.7
	High (0.05)	0	100	100

environments. Our experiments reveal that increased noise significantly hinders radar signal detection, compared to LTE or 5G signal detection. This finding lays the groundwork for our ongoing research, focusing on enhancing the model's robustness for detecting signals within shared spectrum amidst extreme real-world noisy conditions.

Acknowledgement

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