Tu1F-4

# ChirpNet: Noise Resilient Sequential Chirp Based Radar Processing for Object Detection


*Sudarshan Sharma**, Hemant Kumawat*, Saibal Mukhopadhyay

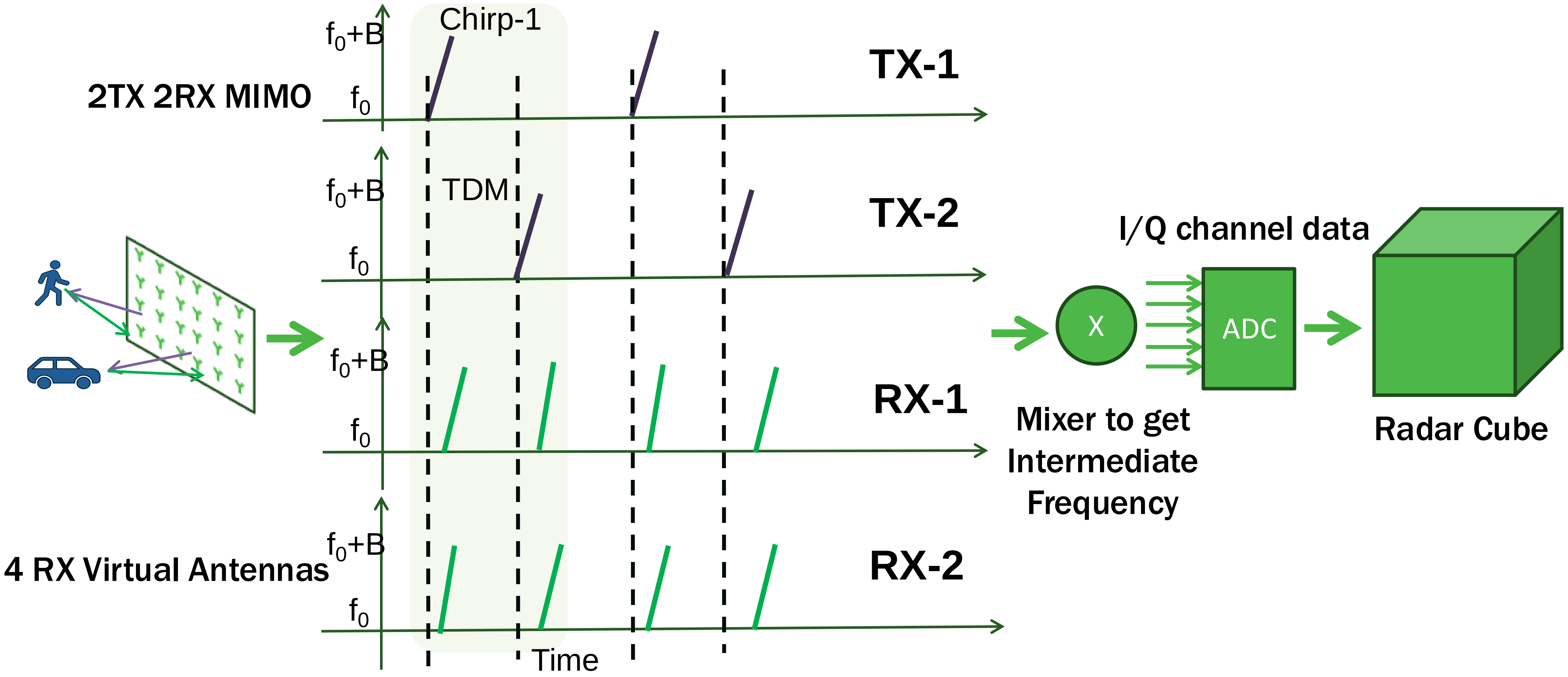
Georgia Tech, Atlanta, GA, USA

*Equally Credited Authors

# Outline

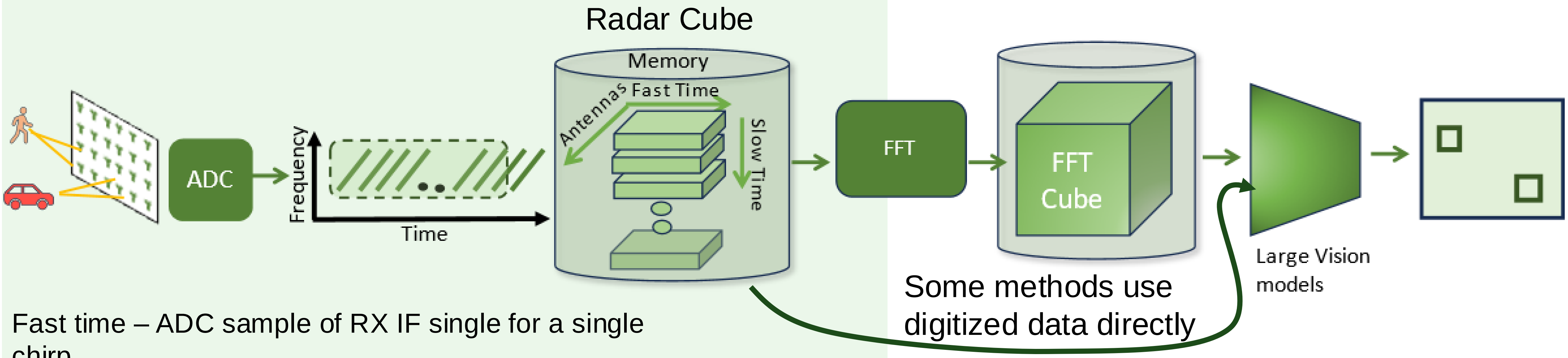
- Background FMCW and Object Detection
- Motivation for ChirpNet
- Dataset Construction
- ChirpNet Architecture
- Empirical Results
- Ablation Studies
- Conclusion
- Future Works

# Background - FMCW Radar




TI Automotive FMCW Radars implements MIMO through time multiplexing through the TX Antenna

# Background- FMCW Radar Based OD



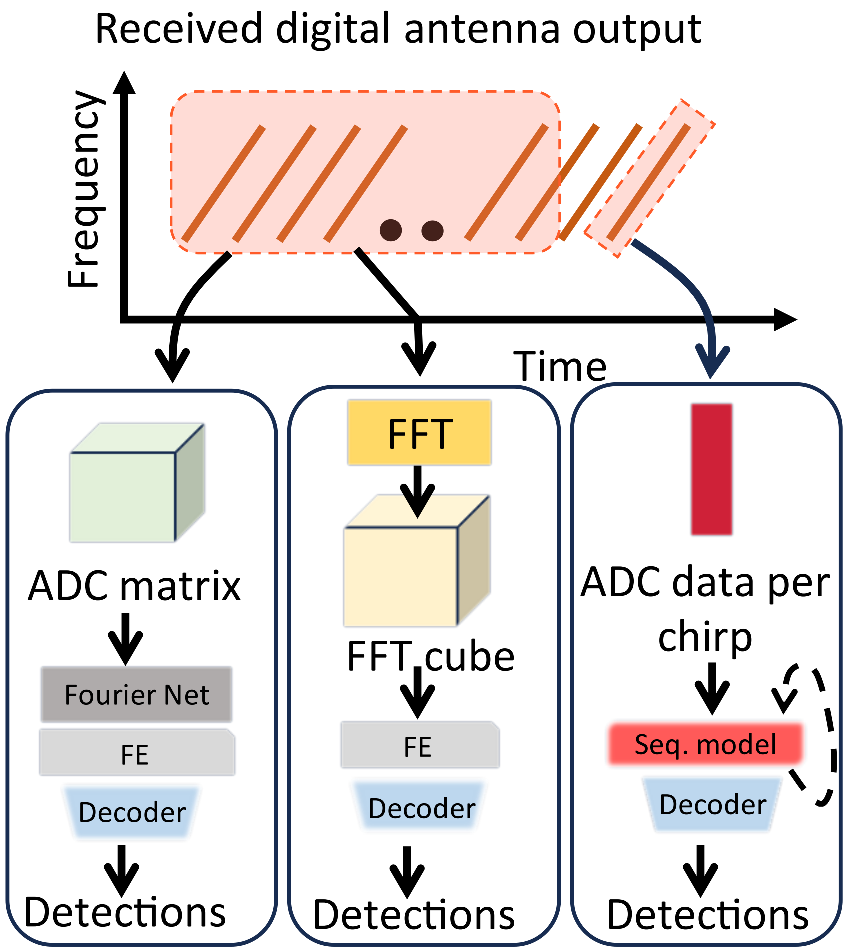

Fast time – ADC sample of RX IF single for a single chirp
Slow Time – Number of Chirps

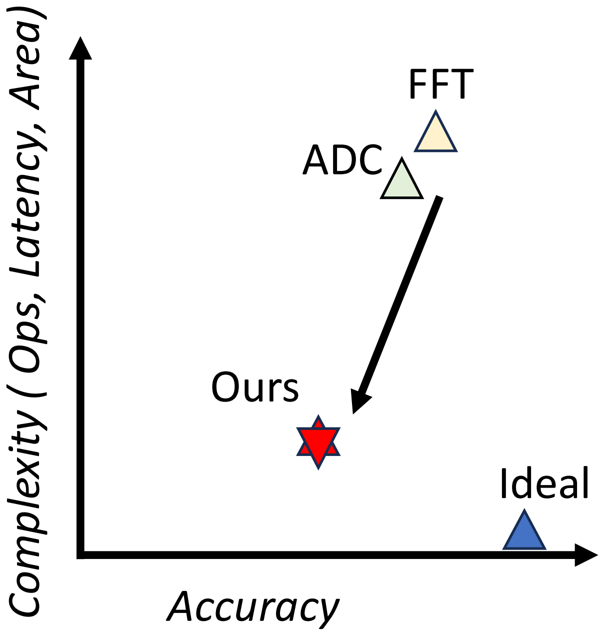
Radar

HOST

**Some methods convert the FFT cube to point clouds. However, unlike LIDAR RADAR point clouds are very sparse which results in lower OD accuracy.**

# Motivation

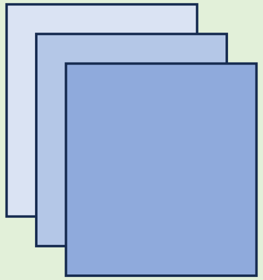



**Can we process raw ADC data directly, with lower computational complexity and competitive accuracy?**

# Dataset Construction

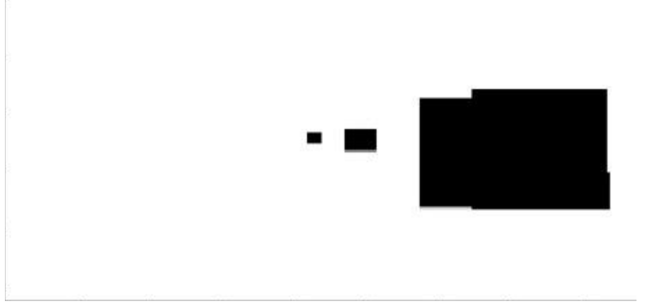
RaDiCal Dataset

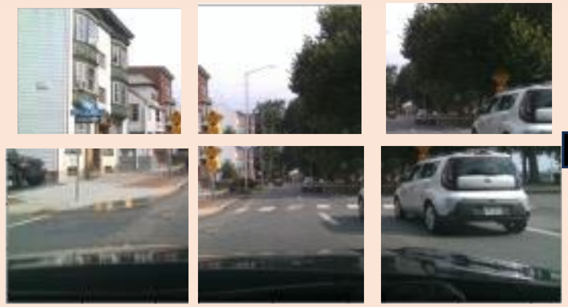


Radar ADC Frames

Camera RGB Image

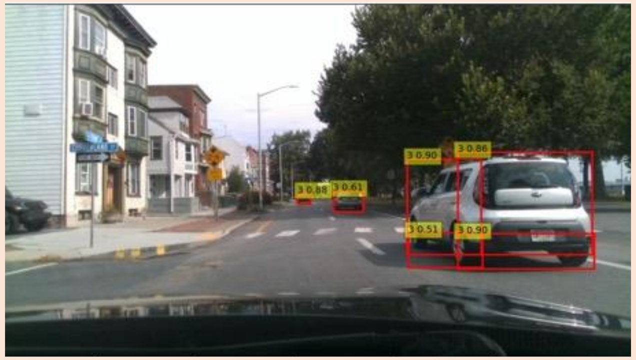
Ground Truth





Tile the Image

Trained Retinanet with Resnet50 as Backbone on COCO dataset



T. -Y. Lim, S. A. Markowitz and M. N. Do, "RaDICaL: A Synchronized FMCW Radar, Depth, IMU and RGB Camera Data Dataset With Low-Level FMCW Radar Signals," in *IEEE Journal of Selected Topics in Signal Processing*, vol. 15, no. 4, pp. 941-953, June 2021, doi: 10.1109/JSTSP.2021.3061270. keywords: {Radar;Radar signal processing;Radar antennas;Radar detection;Time-frequency analysis;Object detection;Radar measurements;Radar;FMCW;sensor-fusion;autonomous driving;dataset;RGB-D;object detection;odometry},

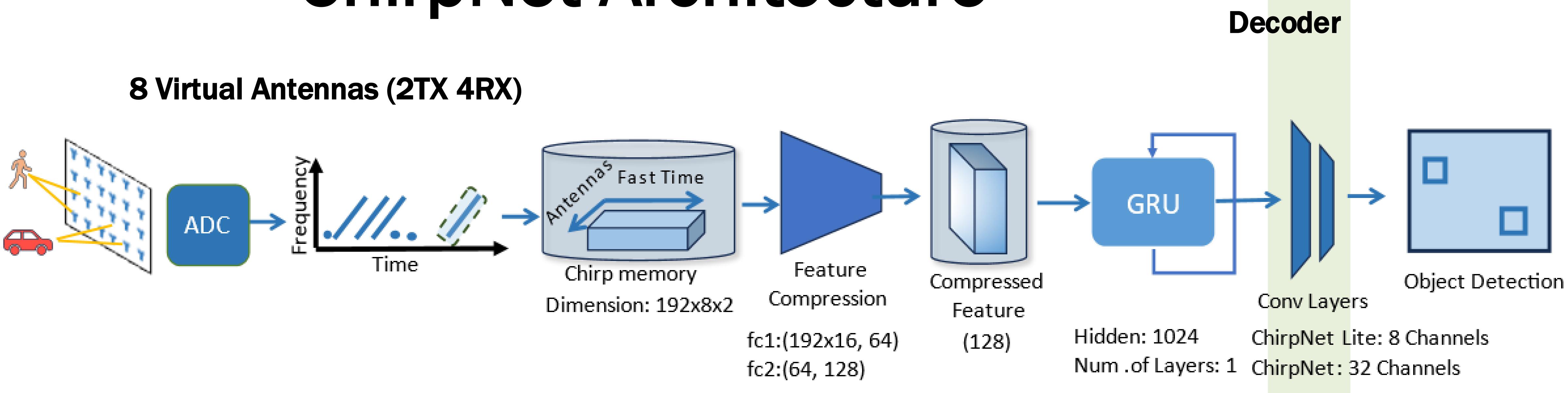
# Dataset Construction- Problems

- The ground truth labels are not hand annotated
  - However, tiling detects all the object
  - But even after Non-Maximum Suppression (NMS) some objects have multiple bounding boxes
- The Radar is placed inside the car which results in some unnecessary detections of the testbed car in the ground truth labels
- Projection/Calibration Matrices to convert the image and depth data to radar space is not available
- Depth measurements has very accuracy for far objects.

# Dataset Construction - Advantages

- Eliminates the need for manual calibration of the image to bird-eye view
- Integrates seamlessly to the post-detection framework such as path planning or control
- Eliminates the need for storing RADAR cube thereby saving storage and compute at the sensor node

# ChirpNet Architecture




**Emulates FFT but performs compression**

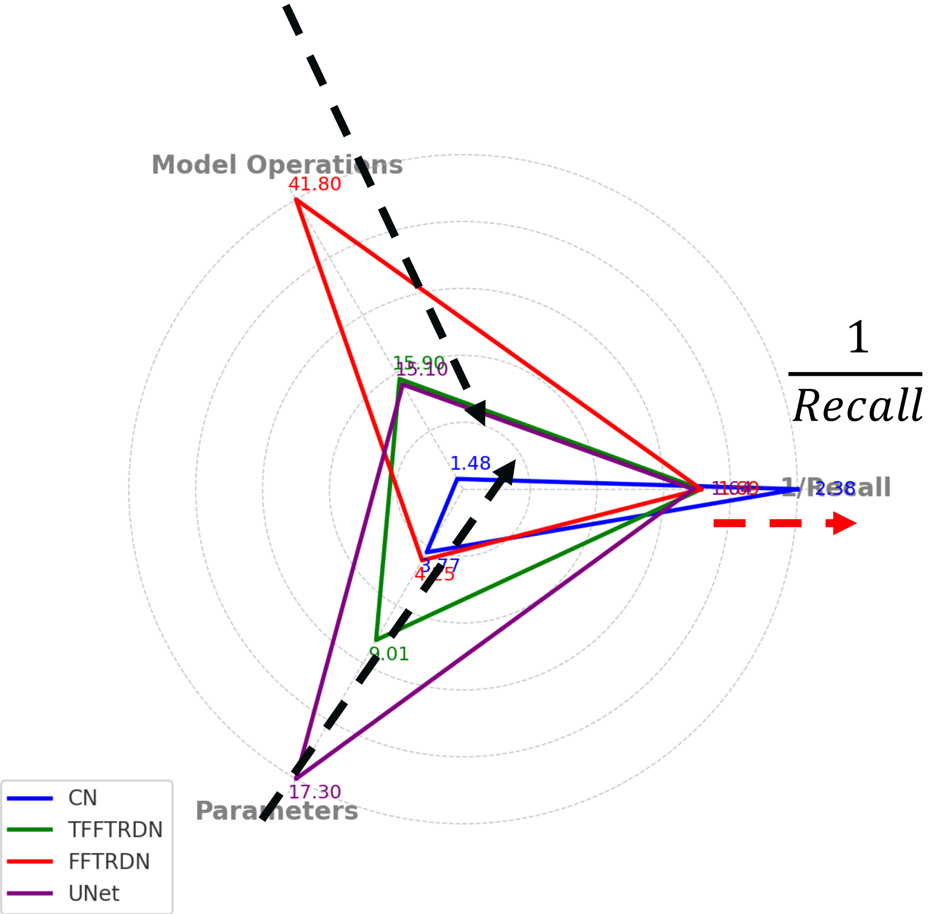
**Gated Recurrent Unit for Chirp Based processing**

- Hyperparameter tuned through ablation study by trying multiple sets of layer parameters.
- We observed a tradeoff in # parameters, # operations and accuracy. Thus proposed ChirpNet and ChirpNet Lite

# Empirical Results- Comparison with Baseline

| Models | CN(Ours) | CNLite(Ours) | TFFTRDN[5] | FFTRDN[4] | UNet[14] |
|---|---|---|---|---|---|
| **Architecture** | | | | | |
| **Input** | ADC/chirp | ADC/chirp | FFT cube | FFT cube | FFT cube |
| **FE Type** | GRU | GRU | Swin Trans. | FPN | Conv |
| **Model Operations (# MACs (G))** | | | | | |
| **FE** | 0.24 | 0.24 | 2.49 | 9.34 | 5.57 |
| **Decoder** | 1.24 | 0.08 | 13.5 | 32.4 | 9.57 |
| **Total** | 1.48 | 0.32 | 15.9 | 41.8 | 15.1 |
| **Model Parameters (M)** | | | | | |
| **FE** | 3.76 | 3.76 | 6.89 | 1.07 | 9.41 |
| **Decoder** | 0.02 | 0.001 | 2.11 | 3.18 | 7.86 |
| **Total** | 3.77 | 3.75 | 9.01 | 4.25 | 17.3 |
| **Accuracy Metrics** | | | | | |
| **Dice-Coeff.** | 0.986 | 0.989 | 0.995 | 0.996 | 0.996 |
| **Recall** | 0.42 | 0.45 | 0.59 | 0.59 | 0.61 |
| **Inference Time (ms)** | | | | | |
| **CPU** | 402.81 | 300.9 | 1340 | 1724 | 1349 |
| **Het-GPU*** | 17.55 | 15.31 | 52.1 | 63.84 | 32.45 |
| **Het-CPU*** | 175.63 | 207.26 | 1274 | 910.02 | 580.34 |

*Het-GPU and Het-CPU denote the execution time on GPU and CPU, respectively, on a CPU-GPU architecture. CPU used - Intel Xeon Gold 6226, GPU used - Nvidia Tesla V100



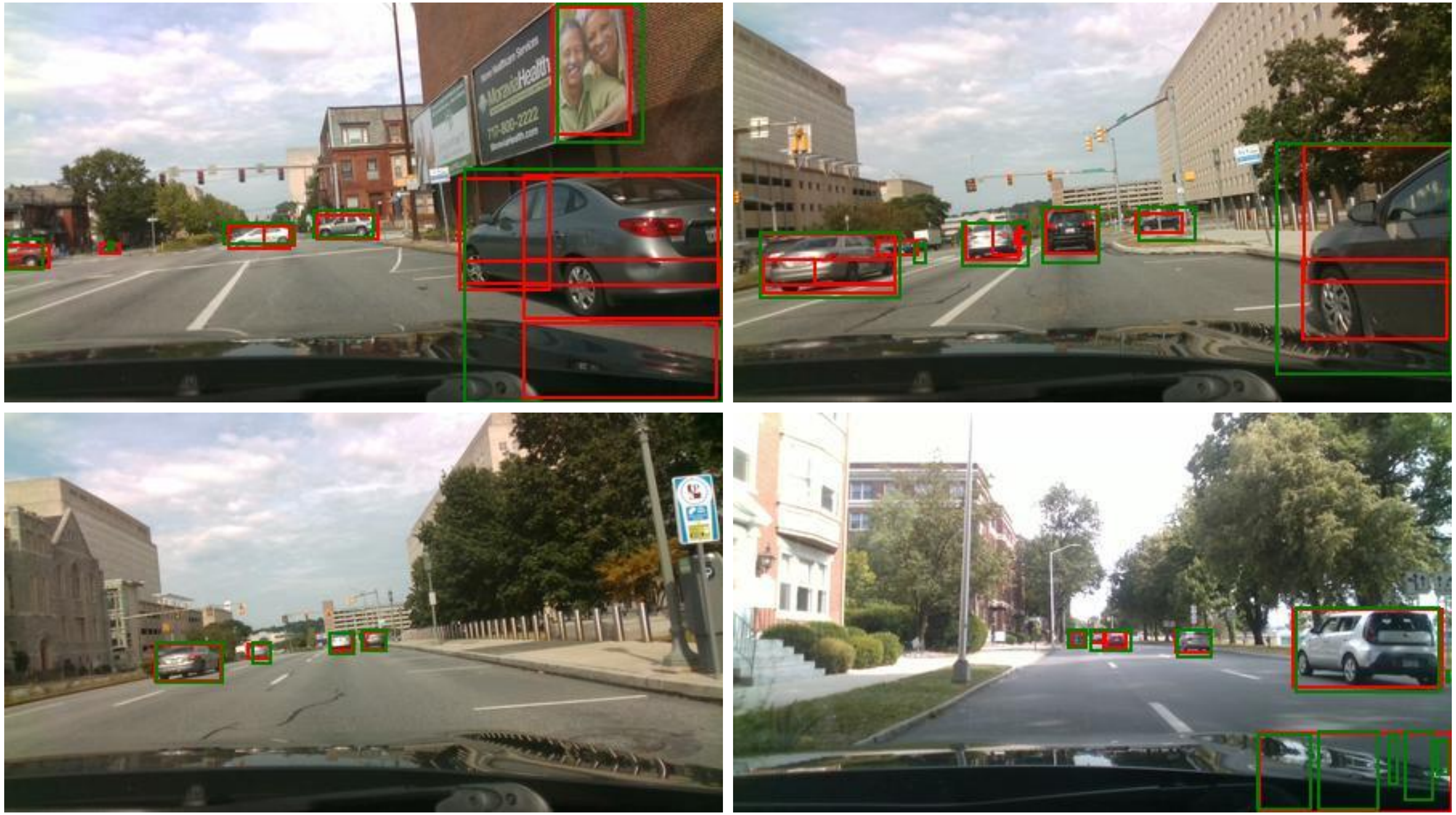

Lower is better for all

~ 3x reduction in Runtime

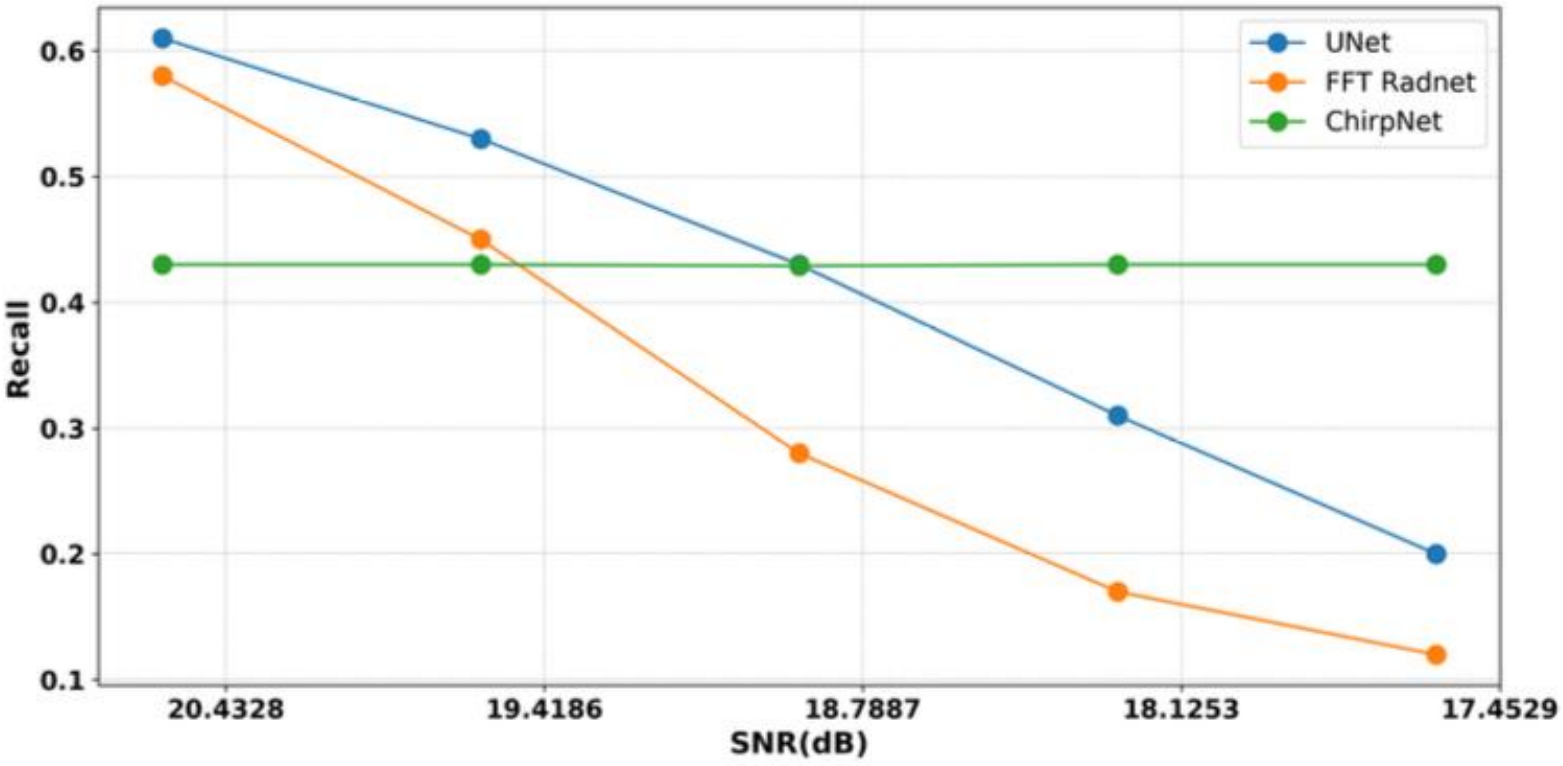
# Empirical Results-Qualitative Analysis

Ground Truth

Predictions

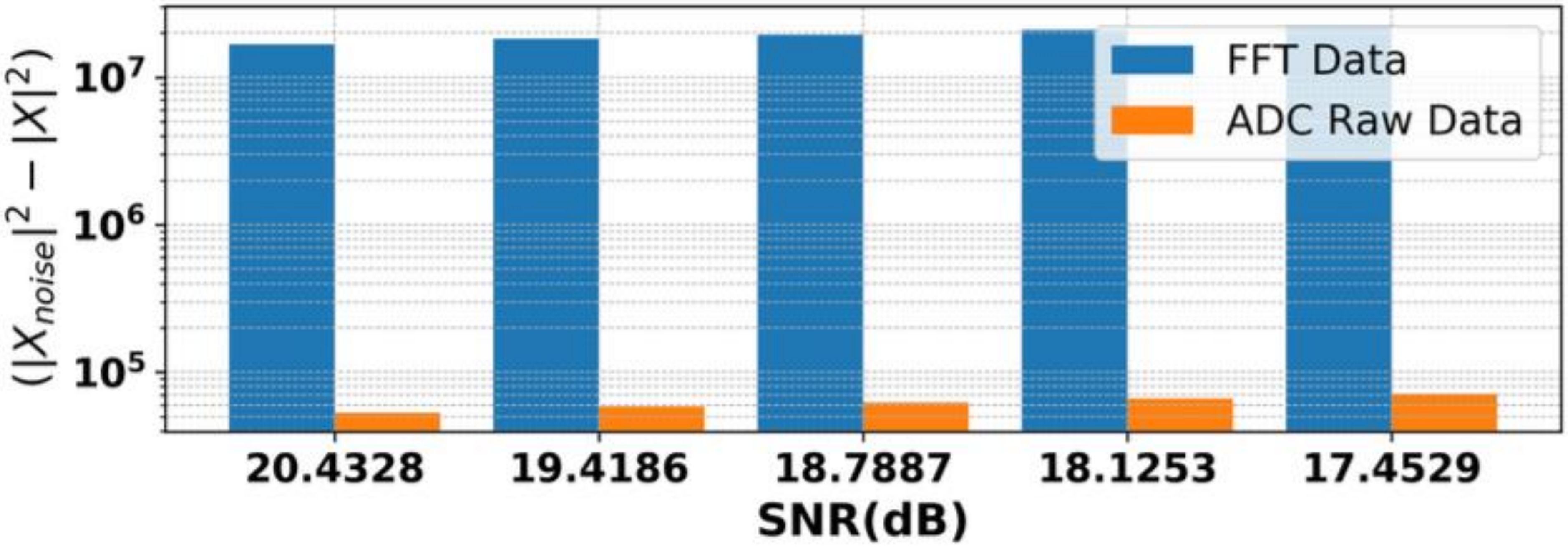


# Empirical Results- Impact of Input SNR - I




**ChirpNet is more robust to SNR degradation!!**

# Empirical Results- Impact of Input SNR - II




**FFT amplifies the input noise to a greater extent which degrades the model performance.**

# Empirical Results- Case study on small Models

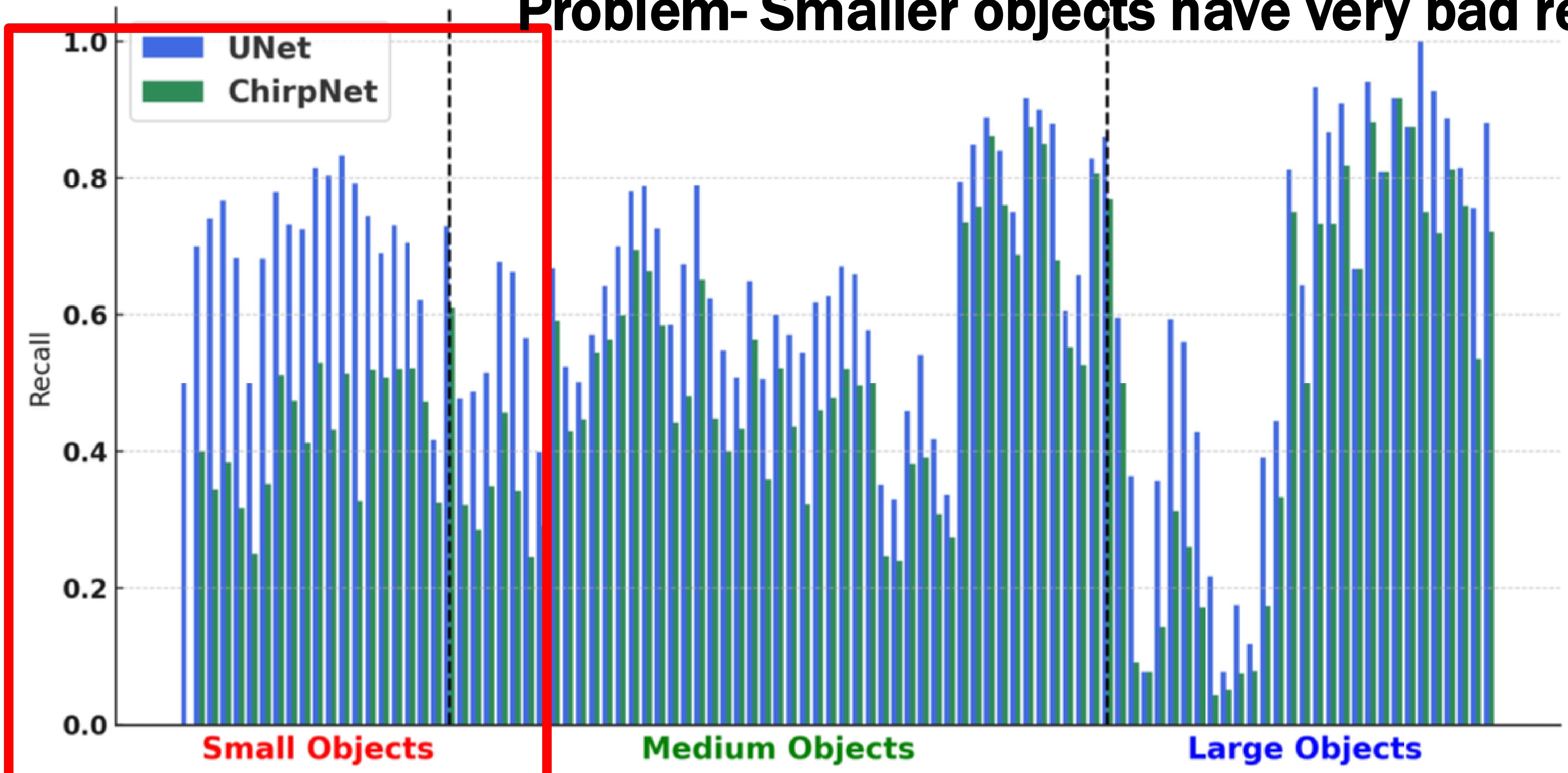
Can smaller models learn from FFTed data?

| Model | Params (M) | #MACs (G) | Recall |
|---|---|---|---|
| UNet_small | 0.48 | 7.88 | 0.02 |
| UNet | 17.3 | 15.1 | 0.61 |

UNet_small comprises of initial two down sampling stages, a single up sampling layer, and a final convolution layer of UNet

# Empirical Results- Ablation Study on Object sizes- I

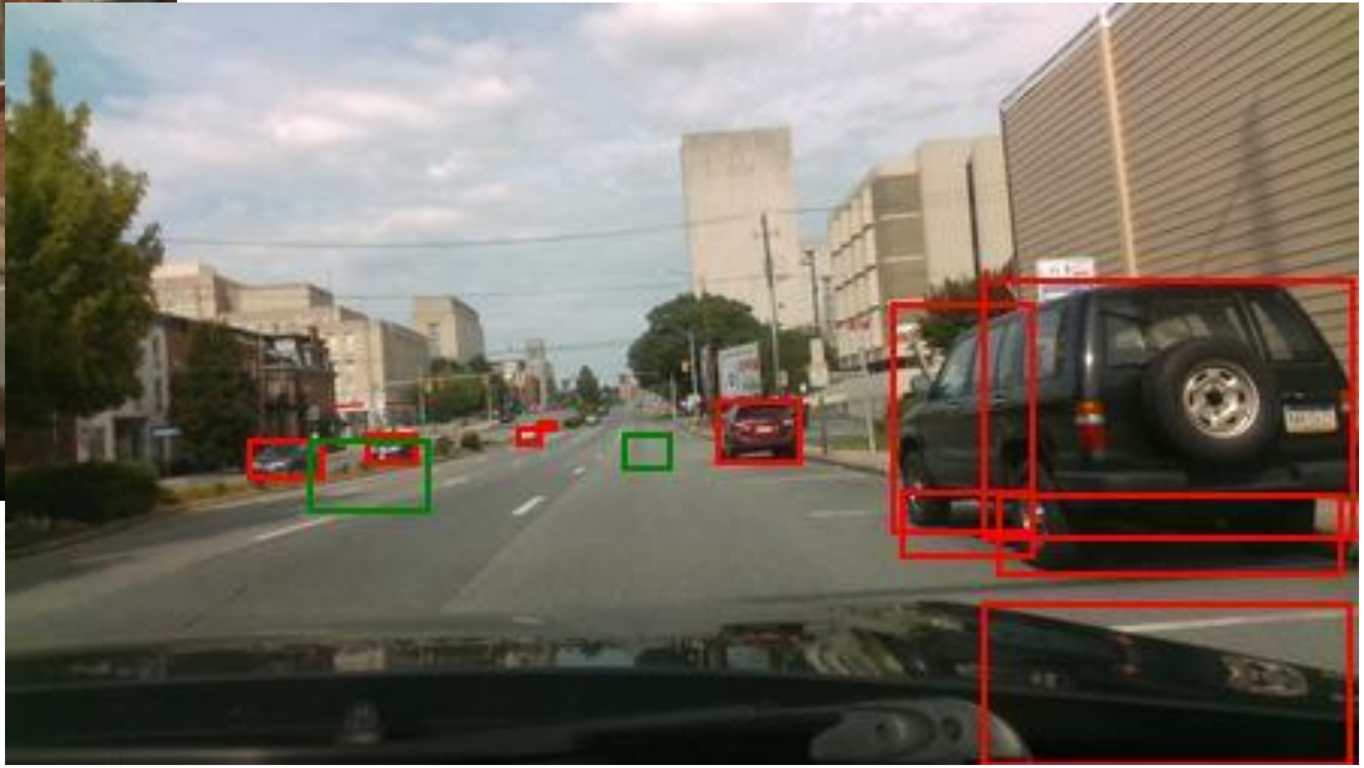
**Problem- Smaller objects have very bad recall**



# Empirical Results- Ablation study on Object sizes - II

Ground Truth

Prediction s



Undetected smaller objects

# Conclusion

- A chirp based sequential radar processing for Object Detection
  - Directly handle raw ADC data from multiple antennas per chirp using a sequential model
  - ChirpNet is more robust compared to prior works with SNR degradation
  - ***15x*** reduction in model complexity
  - ***3x*** reduction in runtime
  - ***2x*** reduction in parameters

# Backups