Machine Learning Techniques for Radar Automatic Target Recognition (ATR)

Chapter 6:
Deep Learning for Single-Target Classification

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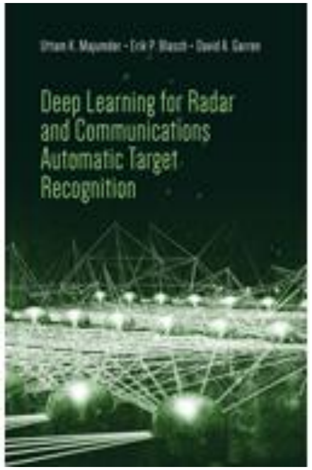
Machine Learning Techniques for Radar Automatic Target Recognition (ATR)

Lecture Outline



1. **Radio Frequency ATR: Past, Present, and Future:** **20 min**
2. **Mathematics for Machine Learning / Deep Learning:** **20 min**
3. Review of ML Algorithms: 25 min
4. **Deep Learning Algorithms:** **30 min**
5. **RF Data for ML Research: 15 min**
6. **DL for Single Target Classification: 25 min**
7. **DL for Many Targets Classification: 15 min**
8. **RF Signals Classification:** **20 min**
9. **RF ATR Performance Evaluation:** **25 min**
10. **Emerging ML Algorithms for RF ATR:** **35 min**

1.5 Deep Neural Networks Architectures and Software

Top 5 DNN Architectures:

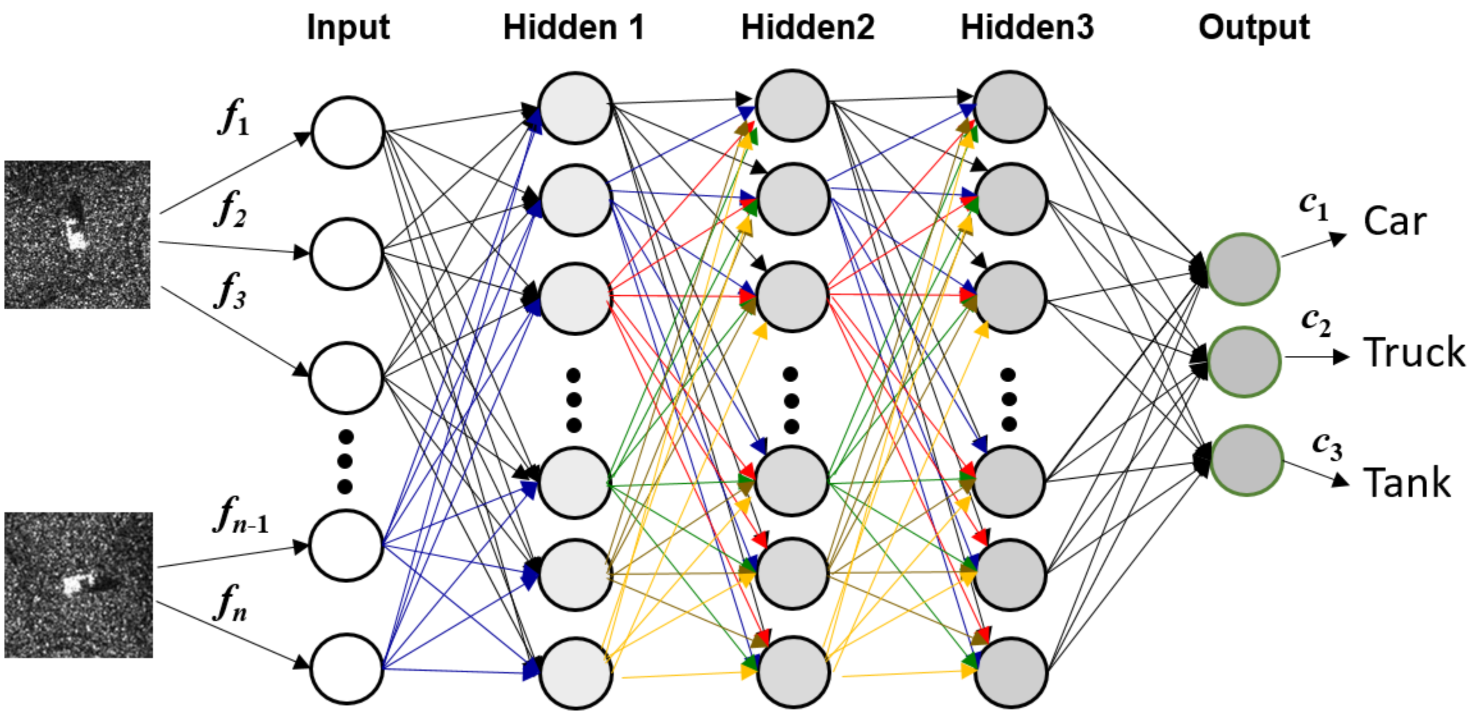
1. LeNet
2. AlexNet
3. VGG
4. GoogleNet
5. ResNet

F. Lei, J. Johnson, S. Yeung, "Lecture 9: CNN Architectures", Stanford School of Engineering. https://www.youtube.com/watch?v=DAOcjicFr1Y

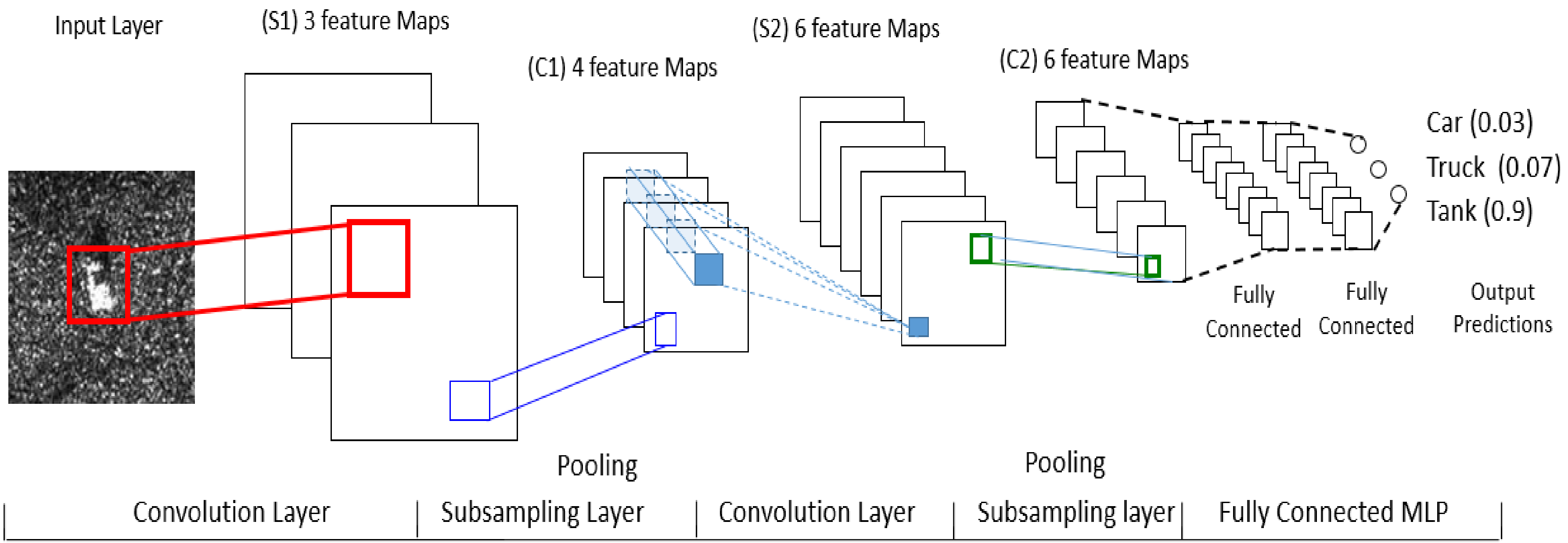
Software/Tools/Hardware:

1. Python, PyTorch
2. Amazon Web Services, Google Colab
3. NVIDIA GPUs

1.5 Deep Neural Networks Model

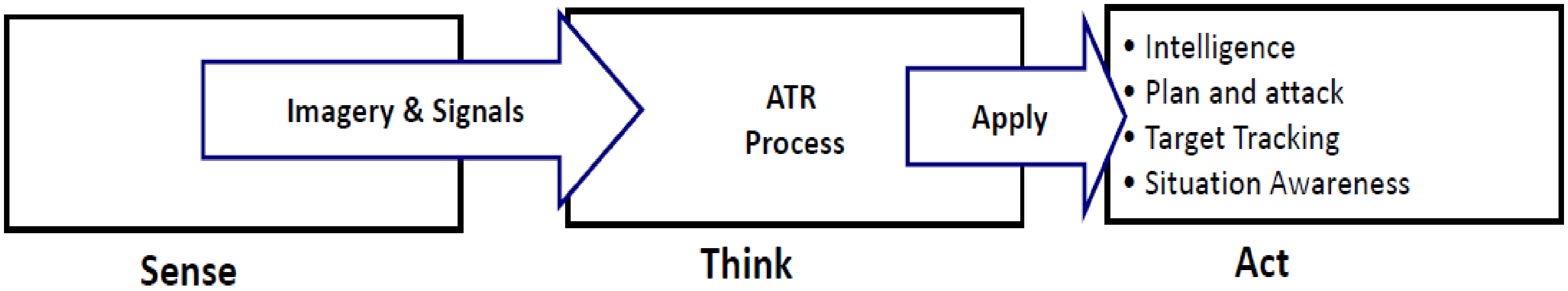


1.5 Convolutional Neural Networks



2. Automatic Target Recognition (ATR)

Definition: Automatic Target Recognition (ATR) is the Computer Aided Process whereby Information from Image Sensor and their sources, in single or multiple modalities, is used to find specific objects in the field of view and report them to subsequent processes to provide Effective Military action.



Detect - There is a target of interest

Classify – Target is a wheeled vehicle

Recognize – Target is a TEL

Identify – Target is a SCUD-B launcher

Screen – Scan the images for TELS

Behavior – Target is moving fast

Detect Change – Find what's new

Cue - Look here

Delimit - TELS can not drive there

Target – Kill target

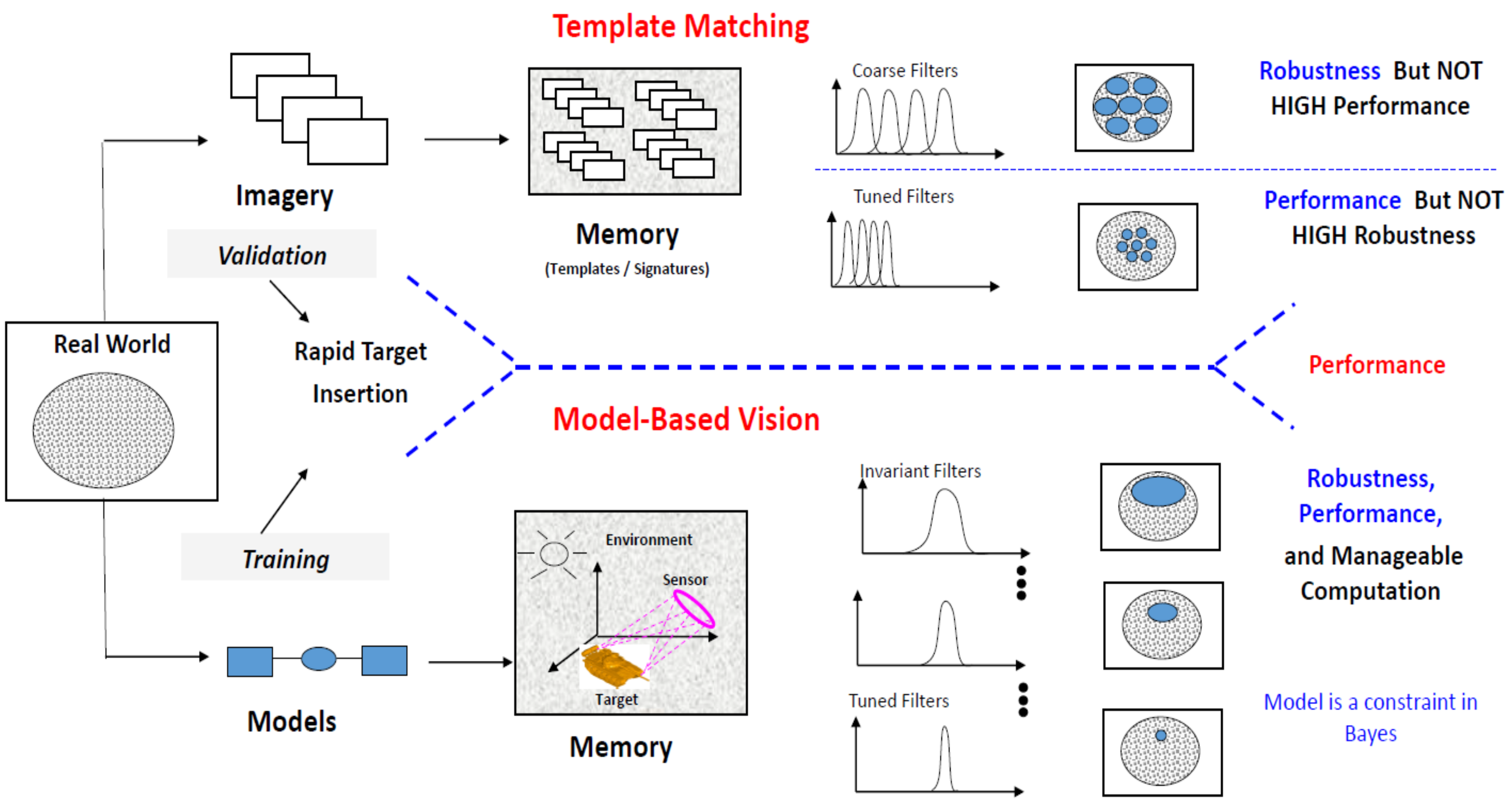
Map – That is a Pine Forest

Track History – Scuds ready to launch

<u>Reference:</u>

Timothy D. Ross, Steven W. Worrell, Vincent J. Velten, John C. Mossing, Michael Lee Bryant, " Standard SAR ATR evaluation experiments using the MSTAR public release data set," Proc. SPIE 3370, Algorithms for Synthetic Aperture Radar Imagery V, (15 September 1998); doi: 10.1117/12.321859

2.1 SAR ATR Approaches



2.2 Previous Approach for SAR Object Classification: DARPA MSTAR Program (1998)

- ***Template-based Matching Approach:***
  - **The training/template formation process consists of registering and estimating the mean target signature over small aspect windows (10 deg)**

$$(x_{opt}, y_{opt}) = \underset{x_s\, y_s}{\mathrm{argmin}}\left(\sum_{x=1}^{N}\sum_{y=1}^{N} |w(x,y)(M_k(x,y) - S(x - x_s, y - y_s))|\right)$$

where:

(x_s, y_s) = Translation Variable
$w(x,y)$ = Binary Mask
$S(x,y)$ = Chip Magnitude

and

$$M_k(x,y) = [(k-1)*M_{k-1}(k-1)/k + k*S(x-x_{opt}, y-y_{opt})]$$

(k = 1 … Number Chips/Template)

  - Classification Cost Measure: Data Processing, Storage, Collection

Reference:
Timothy D. Ross, Steven W. Worrell, Vincent J. Velten, John C. Mossing, Michael Lee Bryant, “ Standard SAR ATR evaluation experiments using the MSTAR public release data set," Proc. SPIE 3370, Algorithms for Synthetic Aperture Radar Imagery V, (15 September 1998); doi: 10.1117/12.321859

2.2 Previous Approach for SAR Object Classification: MSTAR

Results

Table _. Fractional Classification and Rejection Rates ($P_D = 0.9$)

	BMP2	BTR70	T72	Rejections	Confidence
BMP2-1	**0.8256**	0.0923	0	0.0821	+/- 0.020
BMP2-2	**0.7653**	0.1582	0	0.0765	+/- 0.020
BMP2-3*	**0.8929**	0.0408	0	0.0663	+/- 0.020
BTR70-1	0.0073	**0.9197**	0.0073	0.0657	+/- 0.017
BTR70-2*	0	**0.9890**	0	0.0110	+/- 0.017
BTR70-3	0.0182	**0.8869**	0.0036	0.0912	+/- 0.017
BTR70-4	0.0204	**0.8418**	0	0.1378	+/- 0.020
T72-1*	0.0051	0.0102	**0.9592**	0.0255	+/- 0.020
T72-2	0.0667	0.1795	**0.5744**	0.1795	+/- 0.020
T72-3	0.0419	0.1466	**0.6859**	0.1257	+/- 0.020

*: denotes trained object

Reference:
Timothy D. Ross, Steven W. Worrell, Vincent J. Velten, John C. Mossing, Michael Lee Bryant, " Standard SAR ATR evaluation experiments using the MSTAR public release data set," Proc. SPIE 3370, Algorithms for Synthetic Aperture Radar Imagery V, (15 September 1998); doi: 10.1117/12.321859

2.2 Current Deep Learning Approach for SAR Object Classification: DARPA TRACE Program (2016)

Public MSTAR

Ground Plane

REAL	Accuracy
BASELINE / Real network	**0.9961**

COMPLEX	Accuracy
Mag_64	0.9639
Hybrid_64	0.9961
Complex_64_5Z	0.9941
Complex_64	0.9939
Complex_128	**0.9971**
Hybrid_128***	0.9922

Results based on the public MSTAR CDs. 10% of data used for validation.
Obtained from https://www.sdms.afrl.af.mil/index.php?collection=mstar&page=targets

Reference:
SPIE DSS 2016: Public Release, Approved by DARPA

Recent DL Based SAR Target Classification

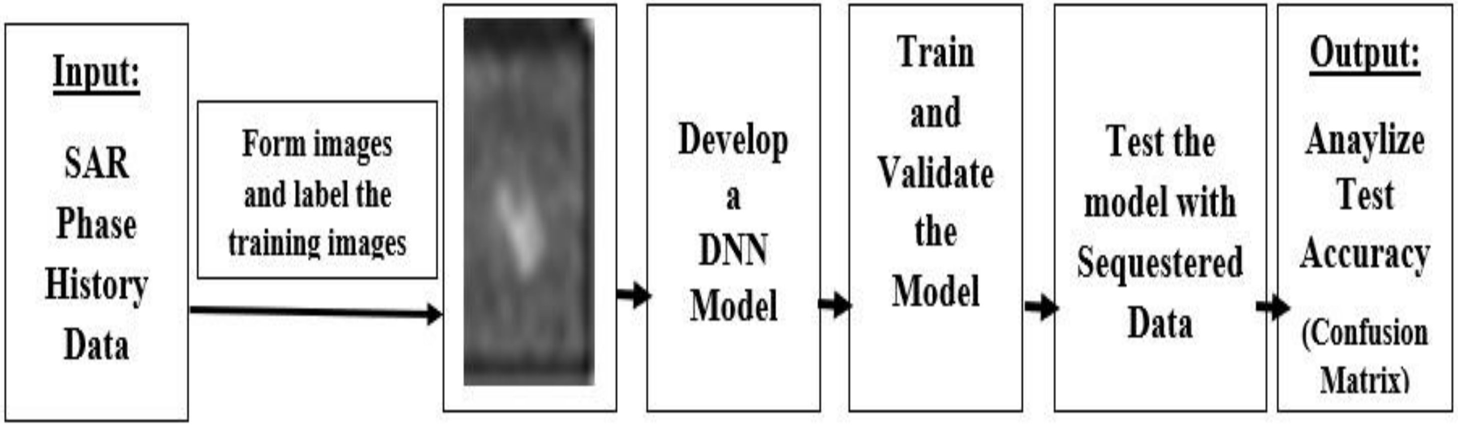
3.1 Single Target Classification

- **Civilian Vehicles Classifications (CV Dome)**

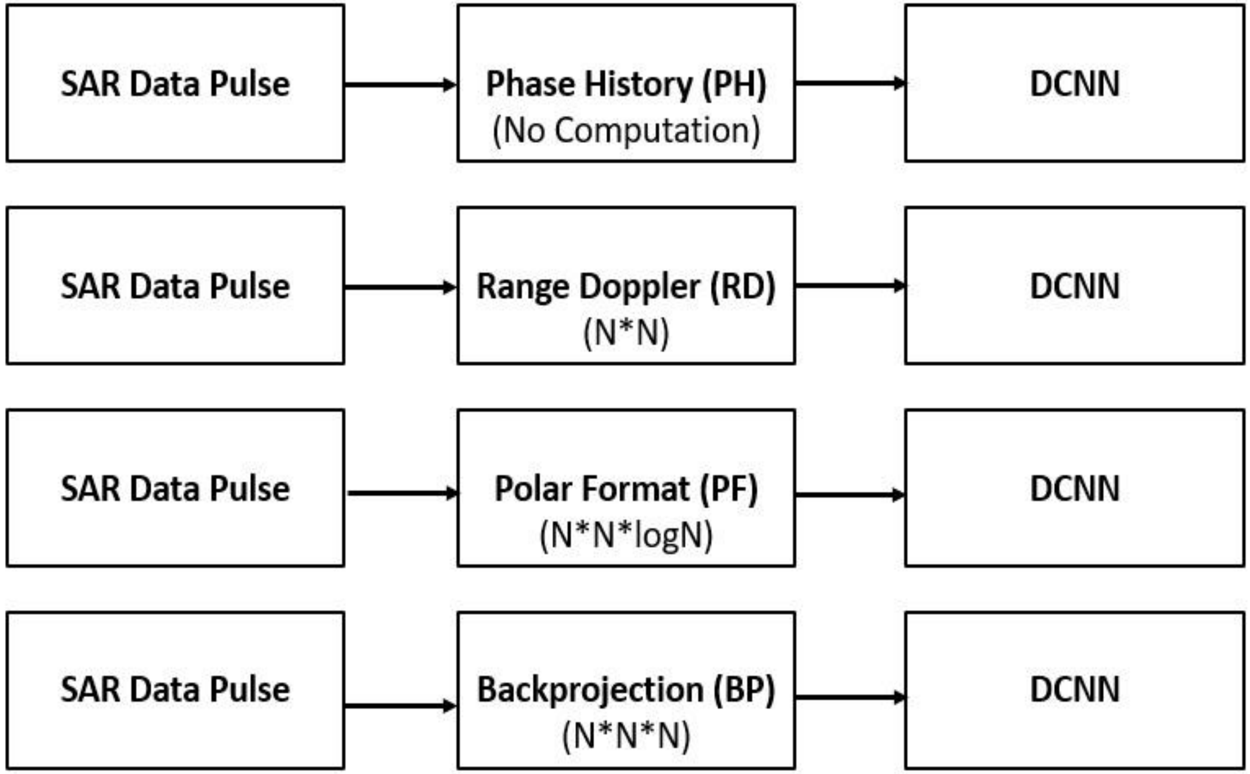
88ABW-2019-1499, 88ABW-2018-2828

- Uttam Majumder, Nate Inkawhich, Erik Blasch. "Deep Learning for Radio Frequency Civilian Vehicles Classification", Proceedings of SPIE, 2019, Baltimore, Maryland, USA.
- Uttam Majumder, Erik Blasch, David Garren, “Machine Learning Techniques for RF Objects Classification”, IEEE Radar Conference Tutorial, Boston, MA, 2019

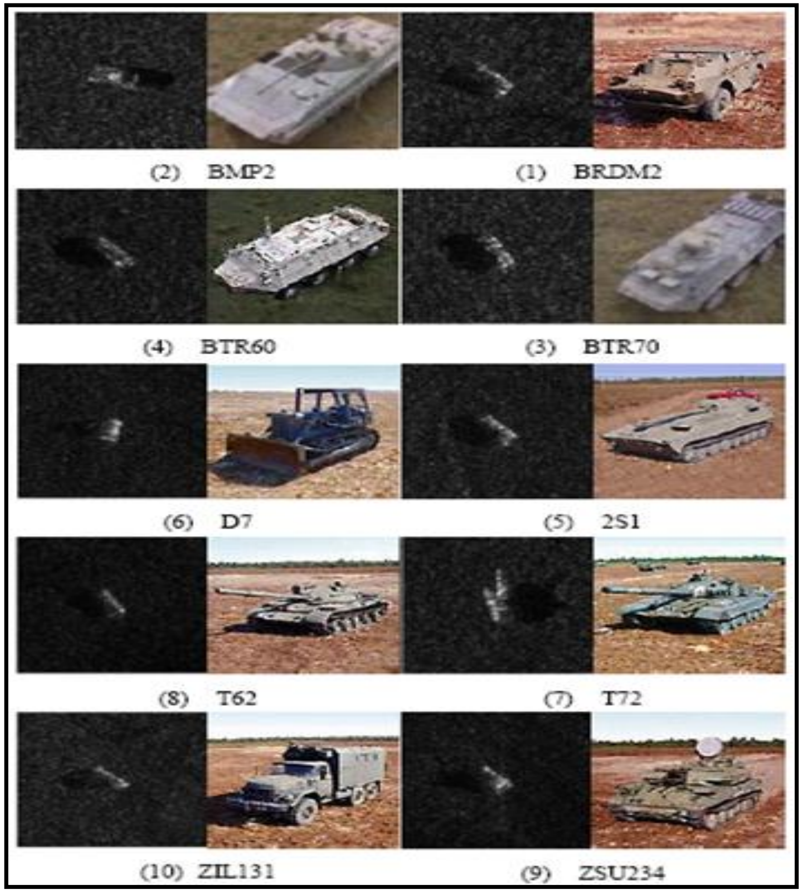
Single Target Classification Steps



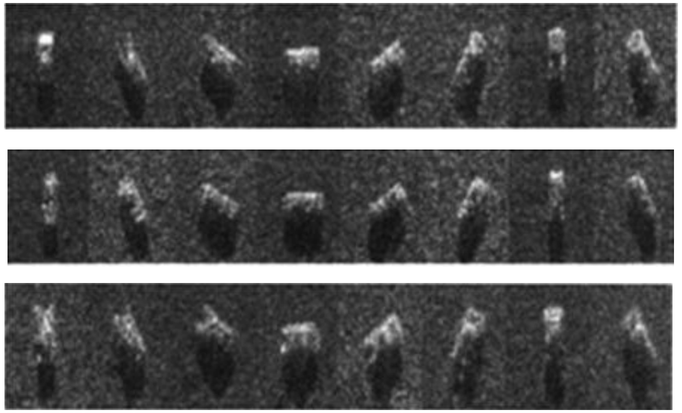
SAR Image Formation



Targets in Video/Electro-optics and SAR



Targets in Various Look Angle



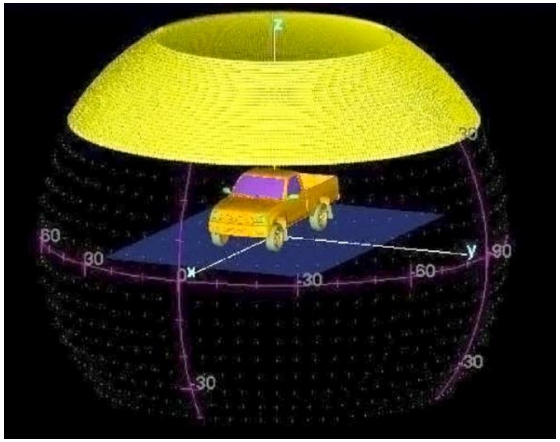
BTR70

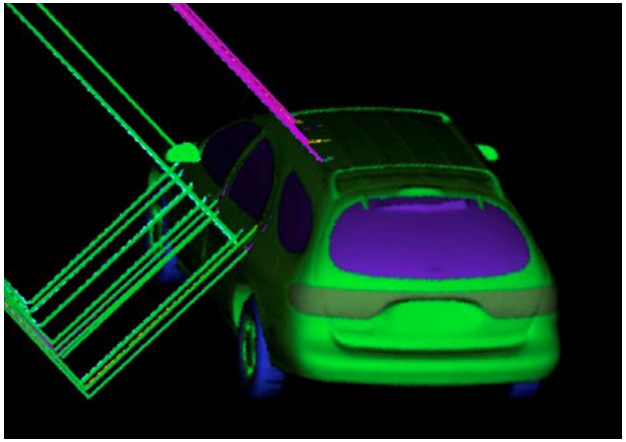
T72

BMP2

3.1 Synthetic RF Dataset

- **Civilian Vehicle Data Domes**
  - **Simulated X-band scattering data** for 10 classes of civilian vehicles
  - Fully polarized far-field monostatic scattering for **360 degrees azimuth** and **elevation angles from 30 to 60** degrees
- **Classes**
  - Camry
  - HondaCivic4dr
  - Jeep93
  - Jeep99
  - Maxima
  - Mazda MPV
  - Mitsubishi
  - Sentra
  - Toyota Avalon
  - Toyota Tacoma





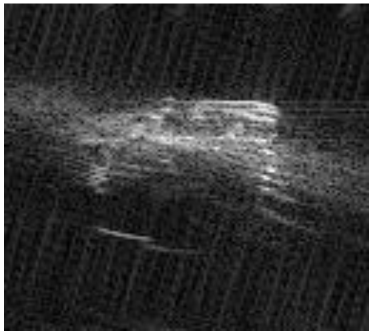
https://www.sdms.afrl.af.mil/index.php?collection=cv_dome

3.1 RF Imaging Methods

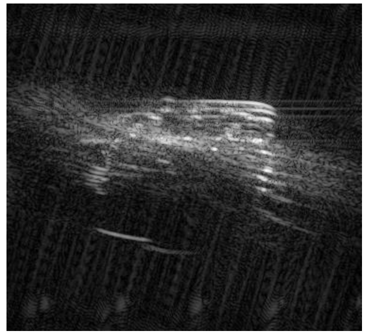
- Once RF data are collected (measured or synthetic), an imaging technique is applied to convert RF phase history data into an image

- Various SAR (RF) imaging techniques provide target/object information at the cost of computational time/burden

3.1 SAR Imaging Methods



Backprojection (BP)
$O(N^3)$



Polar Format (PFA)
$O(N^2 \log N)$

Range Doppler (RD)
$O(N \log N)$

Phase History (PH)
$O(1)$

All images are Jeep93, elevation 40, integration angle 30, starting azimuth 90

- **Four most common RF imaging methods are:**
  - Back-projection (BP)
  - Polar Format Algorithm (PFA)
  - Range Doppler (RD)
  - Phase History (PH) visualization
- **Each technique involves different computational cost and quality of images**

3.1 BP SAR Imaging

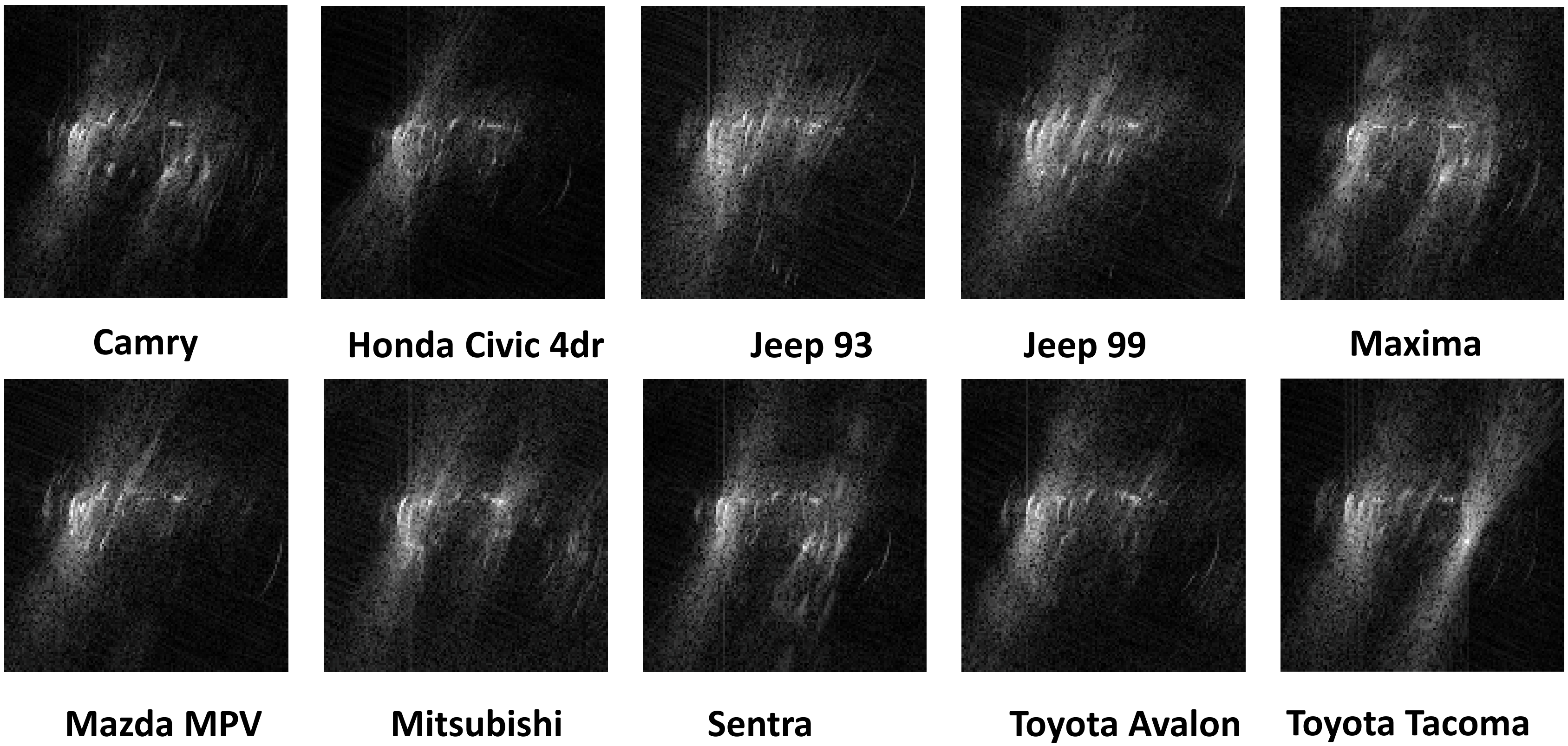


Figure: BP SAR images formed at elevation angle 30, integration angle 50, starting at azimuth 0.

3.1 RF Image Formation

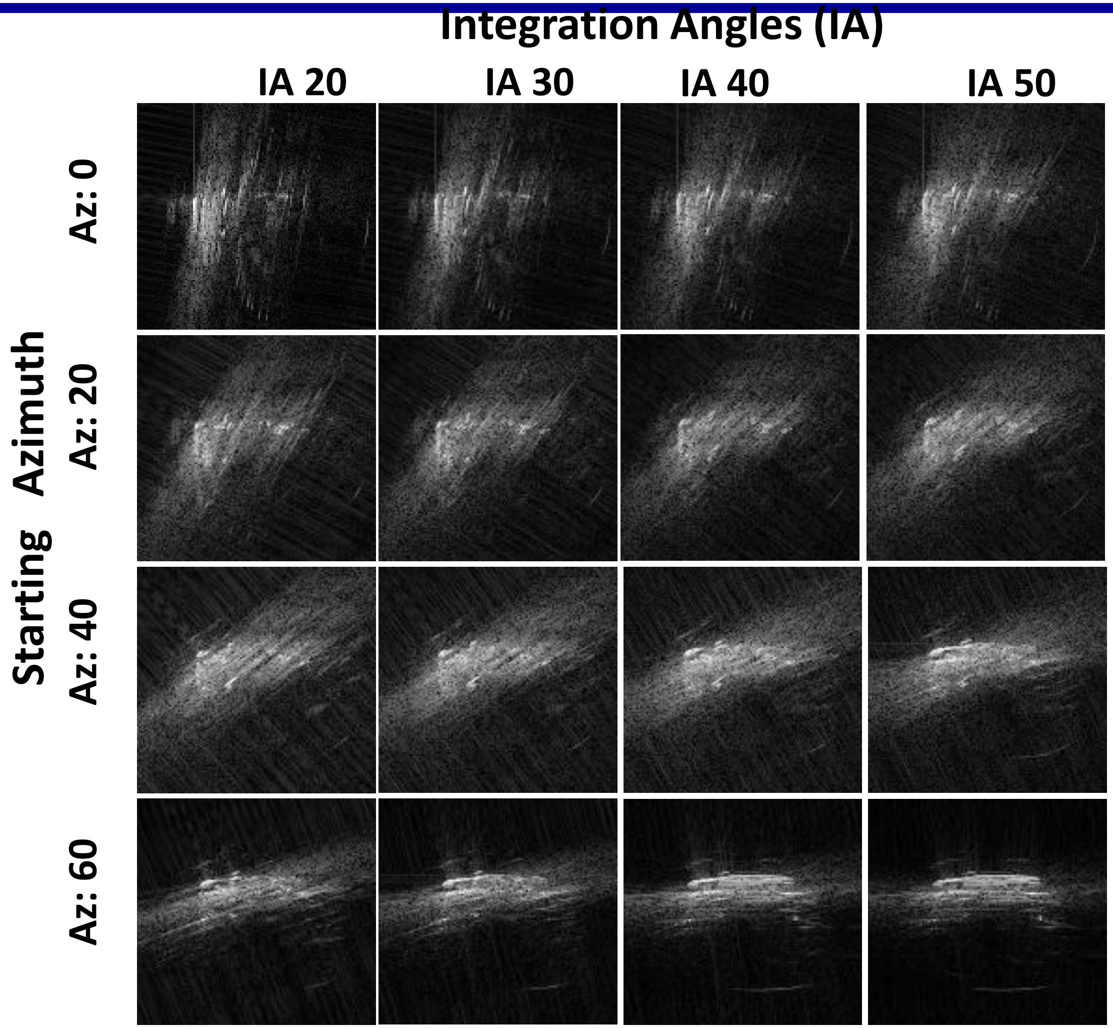
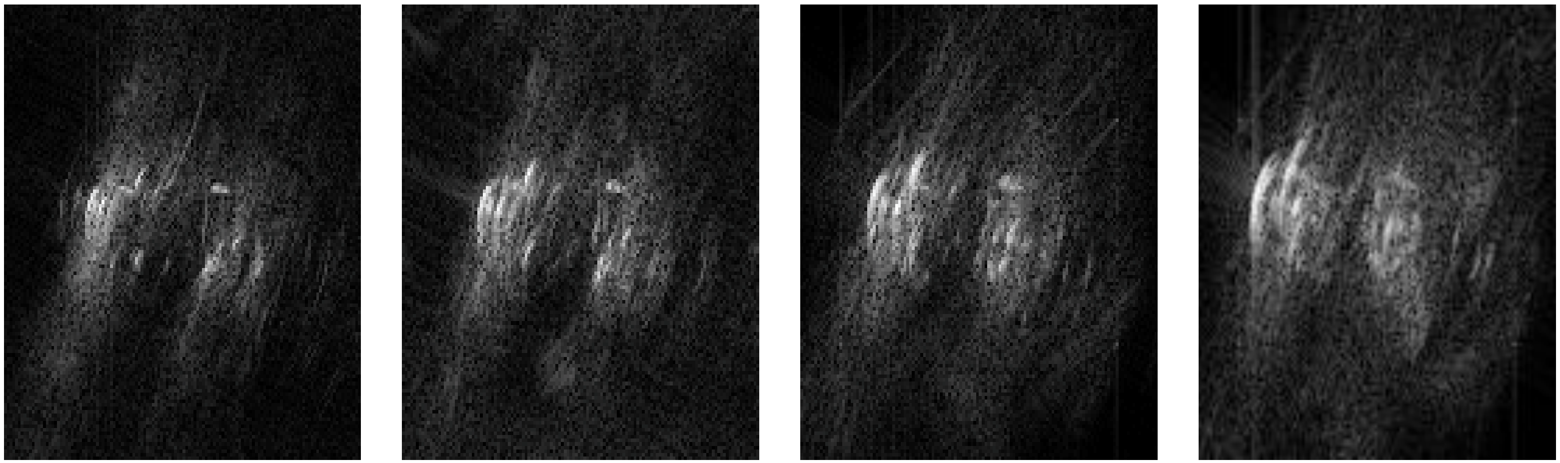


Figure: Starting azimuth and integration angles for Back-projected Jeep93 at elevation 30 degree. This shows impact of look angles and integration angles on finding object features

3.1 SAR Image Formation



El: 30 **El: 40** **El: 50** **El: 60**

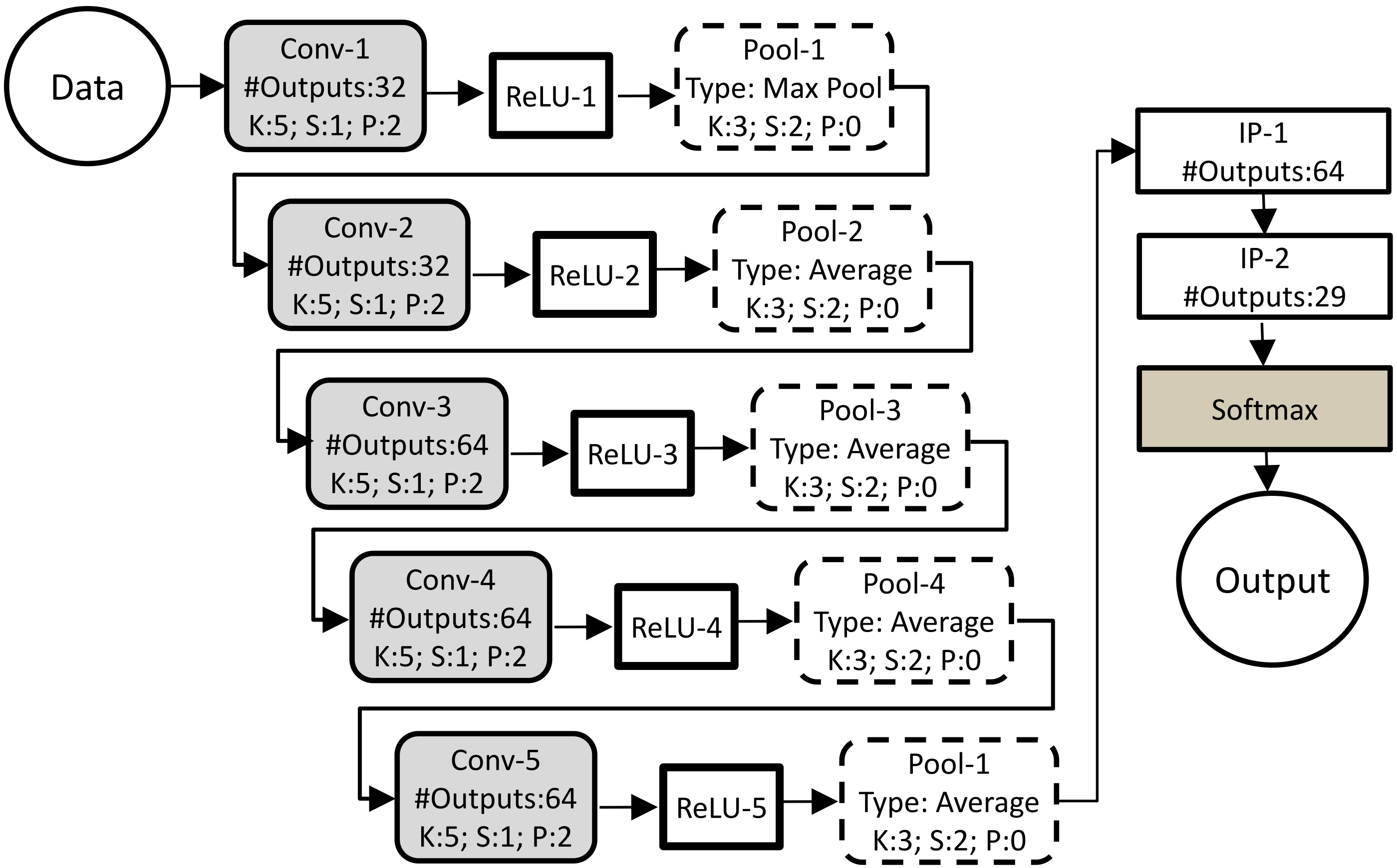
Figure: All images (Camry) are formed by Back-projection, with integration angle 50 and starting azimuth 0. This shows how elevation angle effects the images.

3.1 Deep Learning Models / Architectures

Among Various Deep Learning Models, We Used

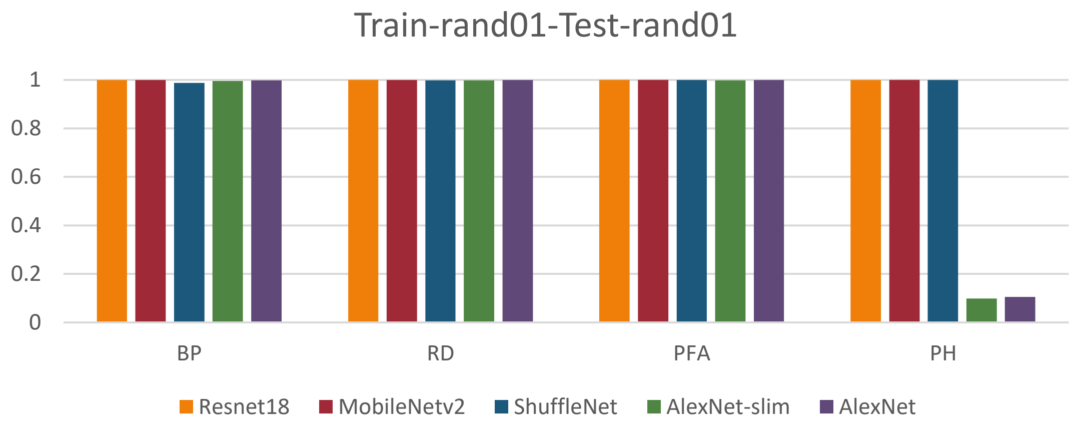
- **ResNet18 (Residual Network)**
- **MobileNetV2 (Good for mobile applications)**
- **ShuffleNet (MobileNet with low power)**
- **AlexNet (ImageNet Classification)**
- **AlexNet-slim**

DNN Architecture

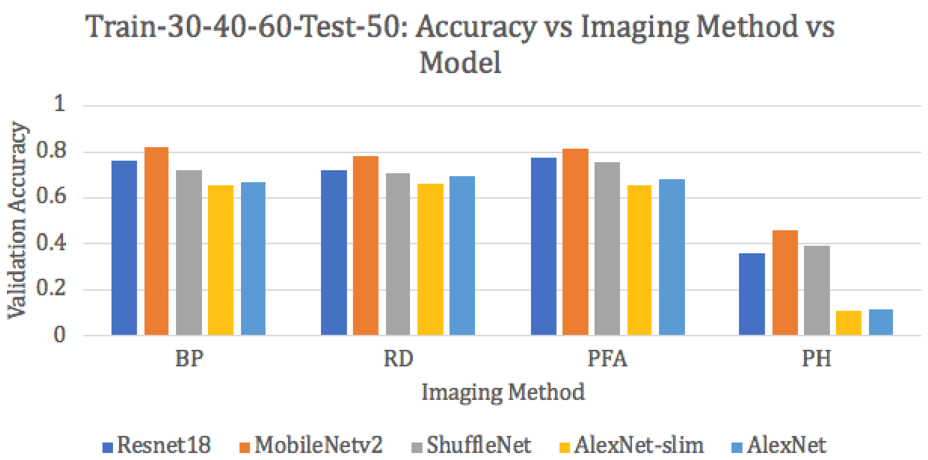


3.1 Overall Results

- **<u>Scenario 1:</u> Have training data to cover all azimuth angles and elevation angles**
  - **Randomly sample a test set from the dataset**
  - **May have *Jeep93_el40.0000_ia30_az90* in training set and *Jeep93_el40.0000_ia30_az92* in test set**



- **<u>Scenario 2:</u> Only have some elevations for training and want to test on other elevations**
  - **Train on elevations 30, 40, 60**
  - **Test on elevation 50**



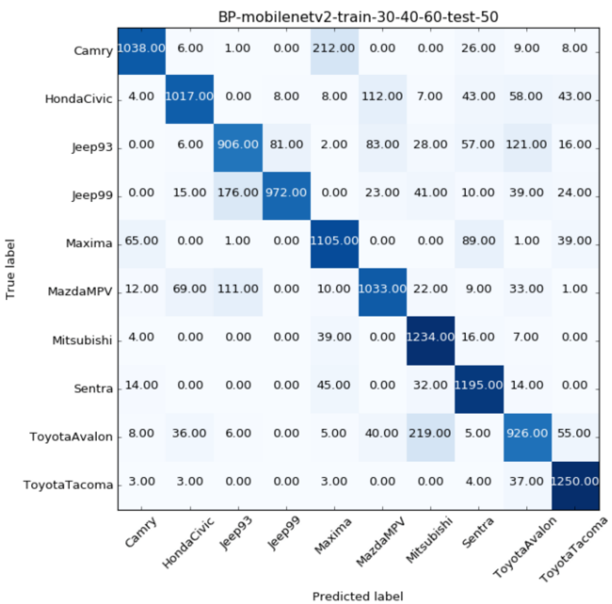
✓ BP, RD, PFA provides comparable accuracy; hence BP Imaging can be avoided (as it is computationally most expensive)

3.1 Confusion Matrices Analysis

- **We pick best overall performing model**
  - **MobileNetv2 to generate confusion matrices (CM)**
- **There will be 12 CM's:**
  - **4 types of data from BP, PFA, RD, and PH imaging**
  - **3 Experiments**
    - **Train on elevation angle: 30,40, and 60; Test elevation angle 50**
    - **Train on elevation angle: 30, 50, and 60; Test elevation angle 40**
    - **Train on random angle (covering all elevation 30, 40, 50, 60) and Test on random angle**

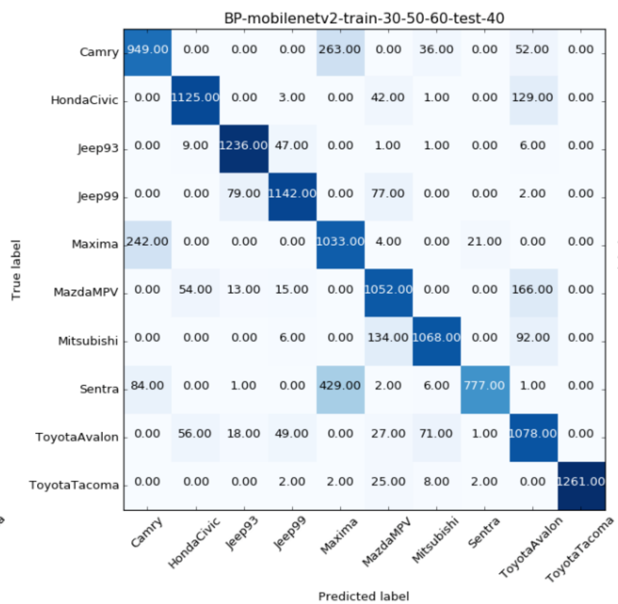
3.1 Confusion Matrices for MobileNetv2 on BP Formed RF Imagery

Train-30-40-60, Test-50



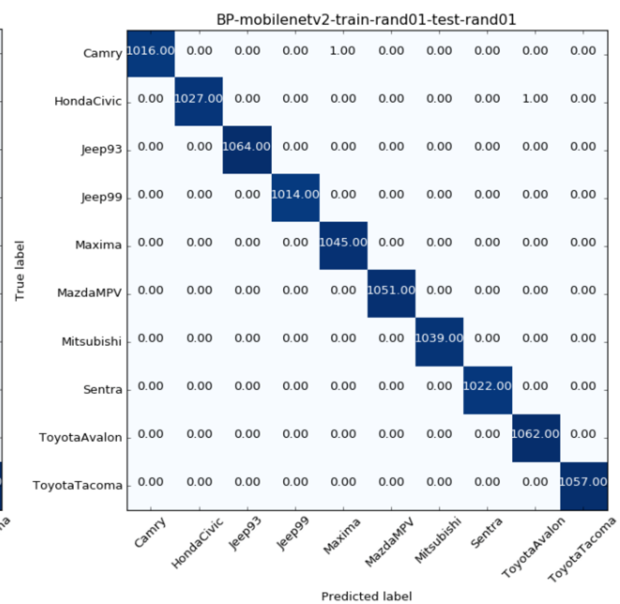
Accuracy: 0.8212

Train-30-50-60, Test-40



Accuracy: 0.8246

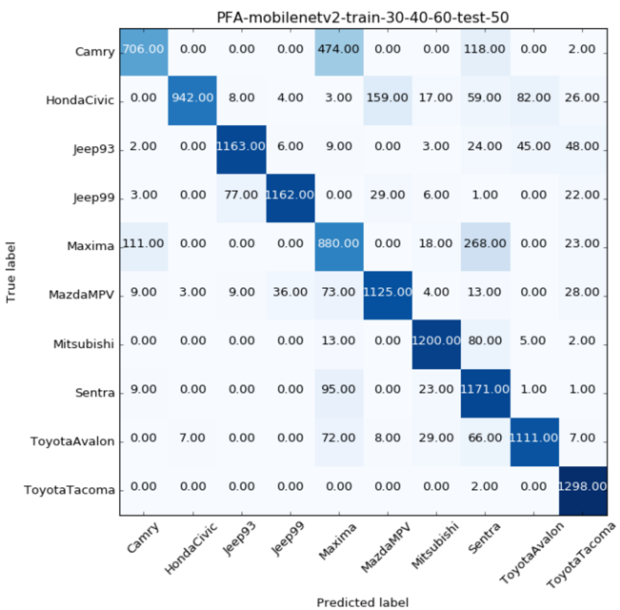
Train-rand01-Test-rand01



Accuracy: 0.9979

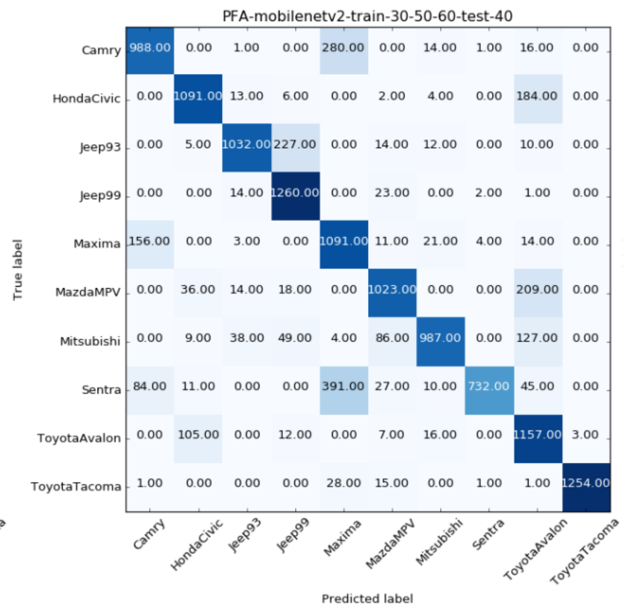
3.1 Confusion Matrices for MobileNetv2 on PFA Formed RF Imagery

Train-30-40-60, Test-50



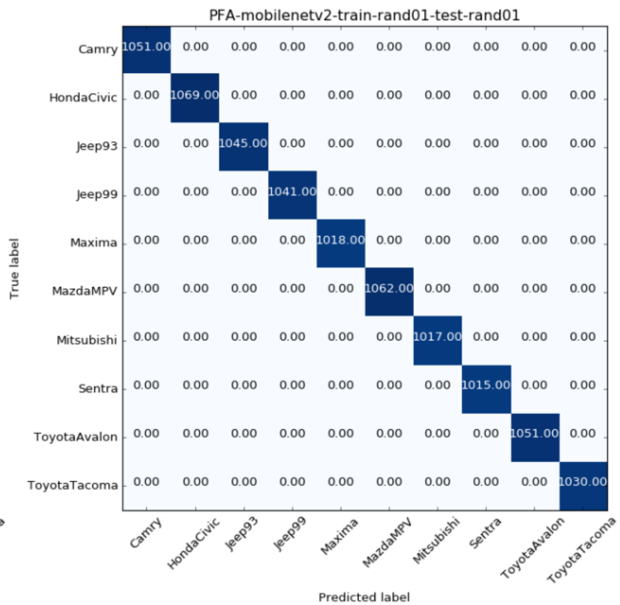
Accuracy: 0.8275

Train-30-50-60, Test-40



Accuracy: 0.8165

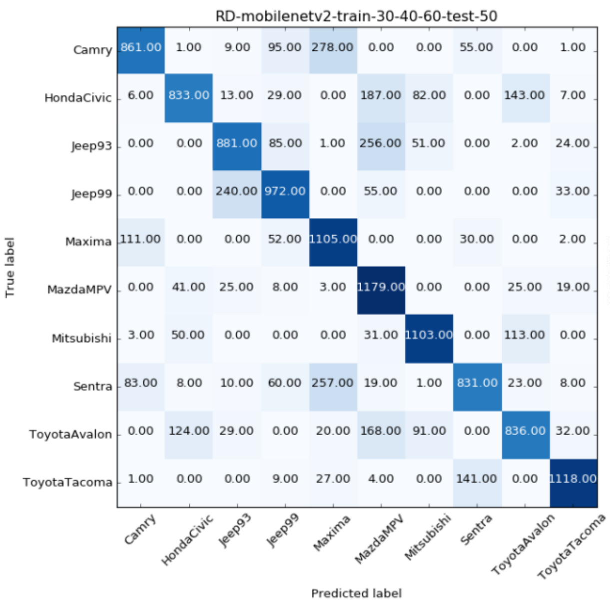
Train-rand01,Test-rand01



Accuracy: 1.0

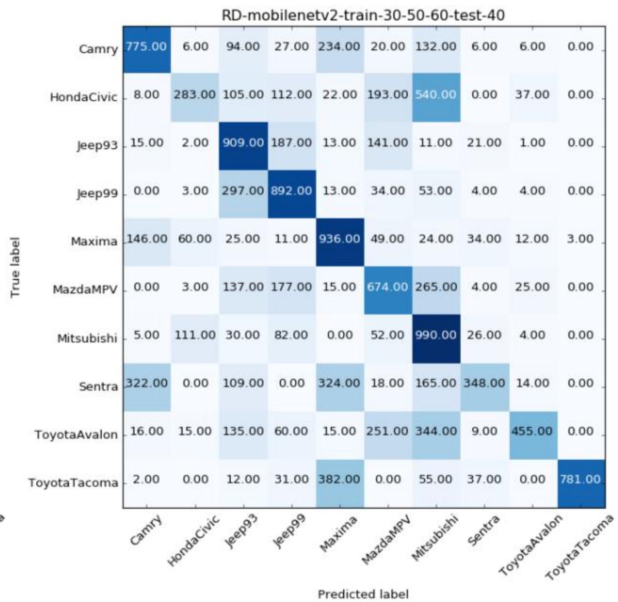
3.1 Confusion Matrices for MobileNetv2 on RD Formed RF Imagery

Train-30-40-60, Test-50



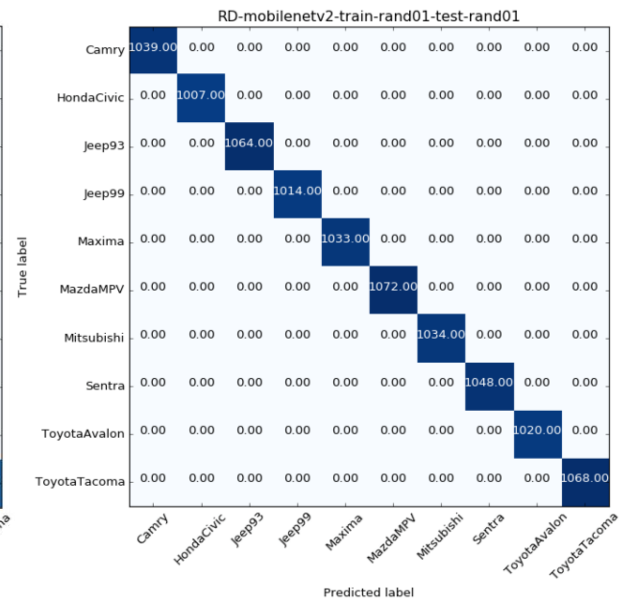
Accuracy: 0.7476

Train-30-50-60,Test-60



Accuracy: 0.5417

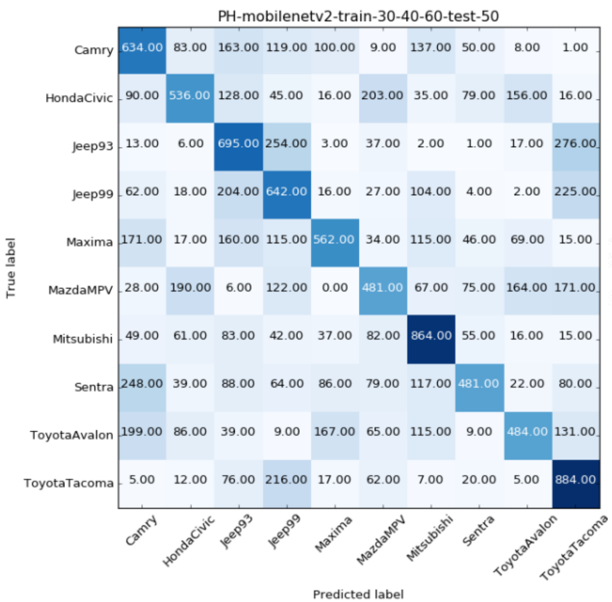
Train-rand01, Test-rand01



Accuracy: 1.0

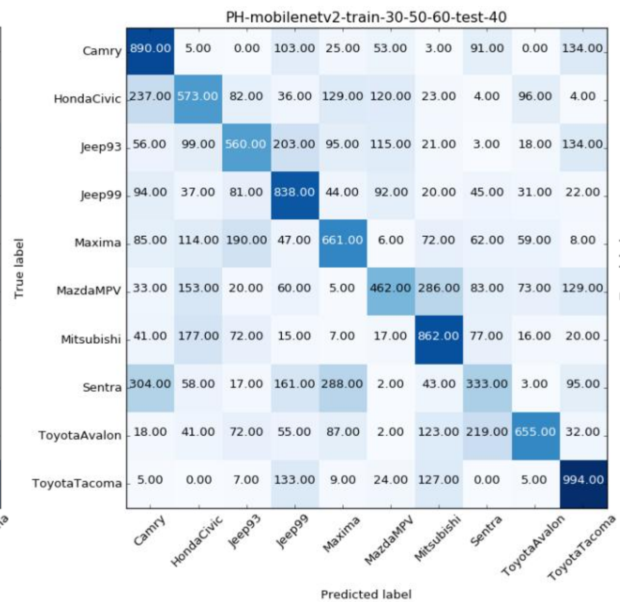
3.1 Confusion Matrices for MobileNetv2 on PH RF Imagery

Train-30-40-60, Test-50



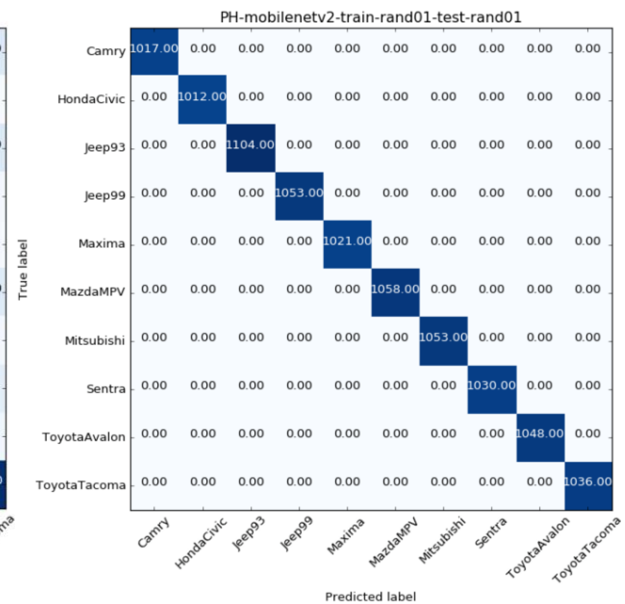
Accuracy: 0.4802

Train-30-50-60, Test-40



Accuracy: 0.5236

Train-rand01, Test-rand01



Accuracy: 1.0

3.1 Conclusions on Civilian Vehicles Classification: (Single Target Classification)

- ✓ Back-projection and Polar Format images look and perform very similarly

- ✓ Random test set performs very well for BP, RD, PFA indicating all are viable options

- ✓ MobileNetV2 and ResNet18 performs well across all imaging techniques

- ✓ Look deeper into the effects of model architecture on performance