SAR Transfer Learning

Catherine Horng – Cornell University

Chris Banas – AFRL/RIEA

THE AIR FORCE RESEARCH LABORATORY

LEAD | DISCOVER | DEVELOP | DELIVER

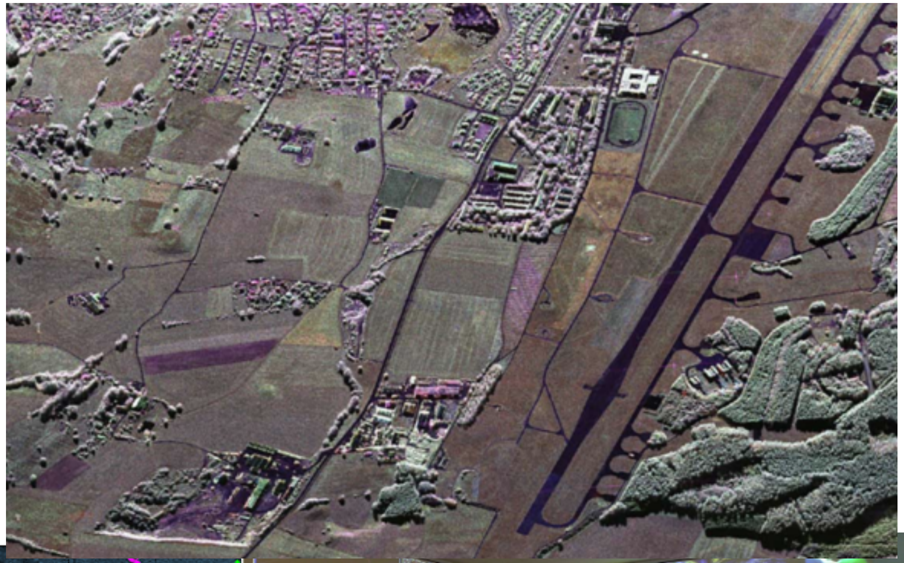
Briefing Contents

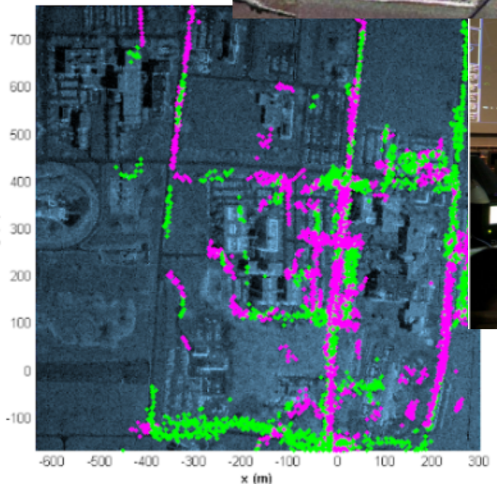
- Overview
  - SAGE Program In-house Team
  - MSTARS Dataset
  - Transfer Learning Experimentation
  - Wrap Up / Lessons Learned

SAGE In-House R&D Team

- Tasked with supporting the SAGE program and program manager.

- Current Research & Development Areas:
  - Machine Learning (ML) and Synthetic Aperture Radar (SAR)
  - Data Analytics for Sensor Exploitation
  - Software Development Support





Project: Transfer Learning with MSTARS (TLIMS)

Purpose

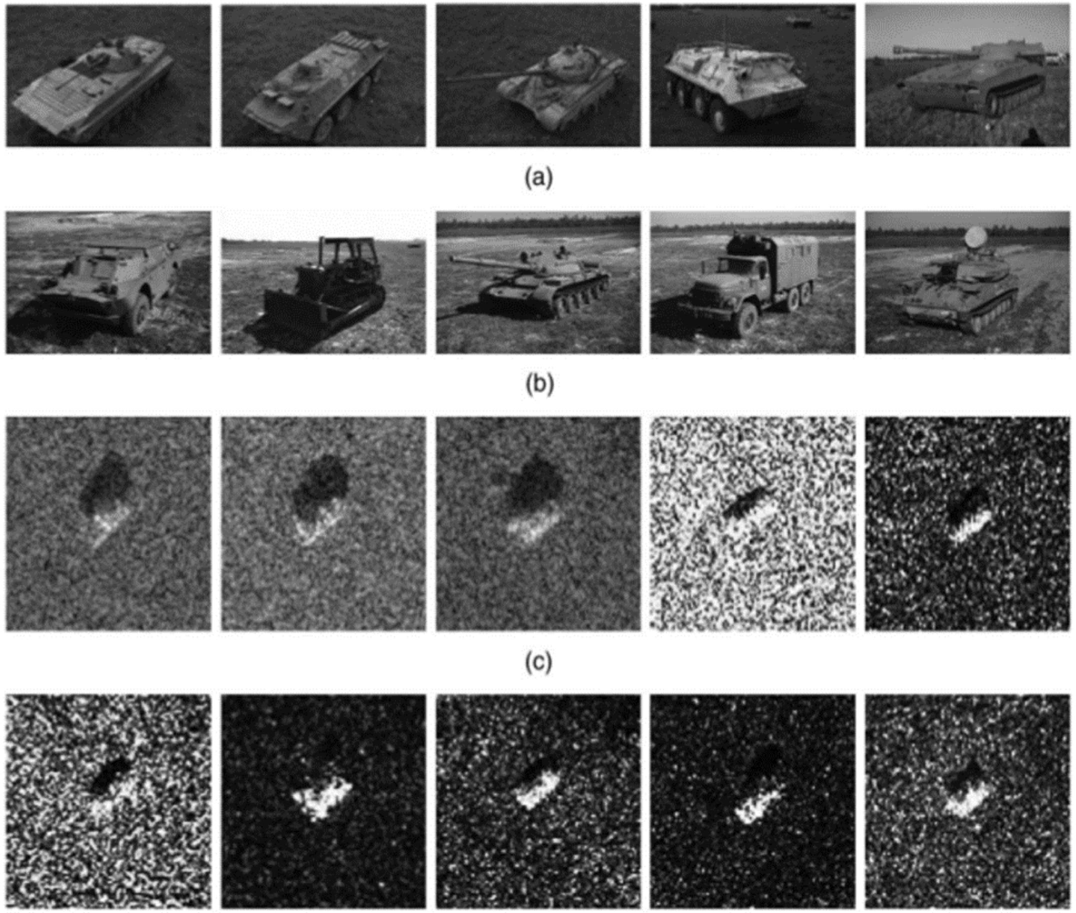
Leverage Transfer Learning approaches to perform image classification on the MSTARS dataset

Research Questions

- Can we use transfer learning techniques with SAR datasets?
- Can we get good performance starting with ImageNet based models for SAR?
- What ImageNet based models would be best to test with SAR?
- What pre-processing is needed to adapt the models?

MSTARS Dataset

- Collected by the Sandia National Laboratory (SNL) in 1995
- Publically Available
- Low Resolution
  - SPOT SAR
  - 1-meter resolution
- Still Relevant
  - Gao, Fei, et al. "A new algorithm for SAR image target recognition based on an improved deep convolutional neural network." *Cognitive Computation* 11.6 (2019): 809-824.
  - Huang, Guoquan, et al. "A novel group squeeze excitation sparsely connected convolutional networks for SAR target classification." *International Journal of Remote Sensing* 40.11 (2019): 4346-4360.
  - Lewis, Benjamin, et al. "A SAR dataset for ATR development: the Synthetic and Measured Paired Labeled Experiment (SAMPLE)." *Algorithms for Synthetic Aperture Radar Imagery XXVI*. Vol. 10987. International Society for Optics and Photonics, 2019.
  - …



(a)
(b)
(c)
(d)

MSTARS Dataset Contd…

Targets (# of)	Target Description	Amount
T-72 (3)	T-72 Tank	3 replicate targets: each collected at 15 & 17 degree dep. angles and full aspect coverage
BMP2 (3)	Infantry Fighting Vehicle	3 replicate targets: each collected at 15 & 17 degree dep. angles and full aspect coverage
BTR-70 (1)	Armored Personnel Carrier	1 target: collected at 15 & 17 degree dep. angles and full aspect coverage
Slicy (1)	Multiple simple geometric shaped static target	CAD Model November '96 Imagery: TBD in Jan '97

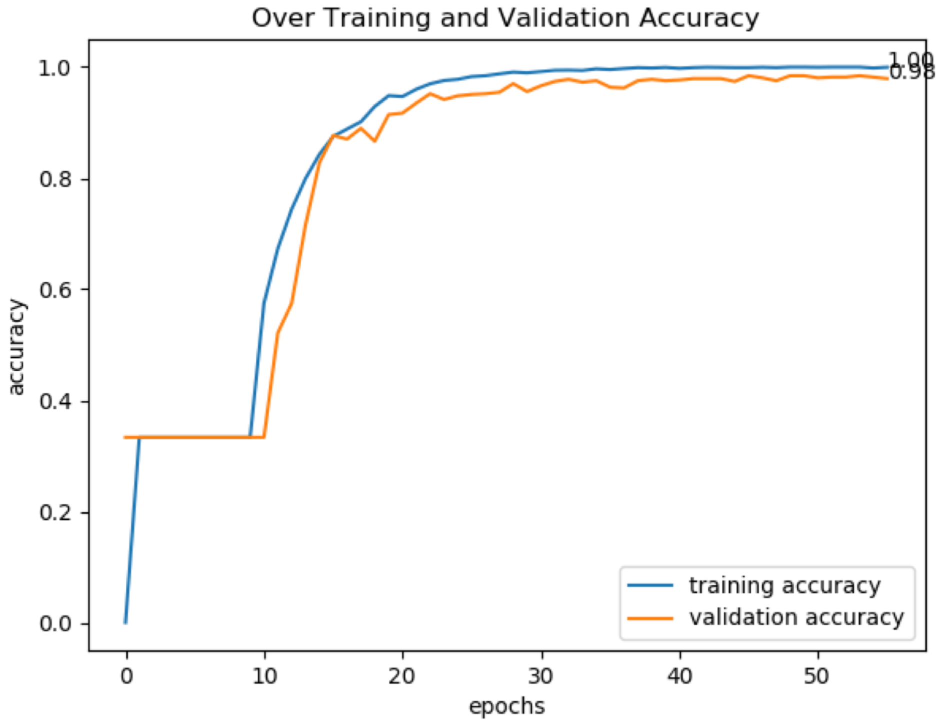
Approach: Transfer Learning

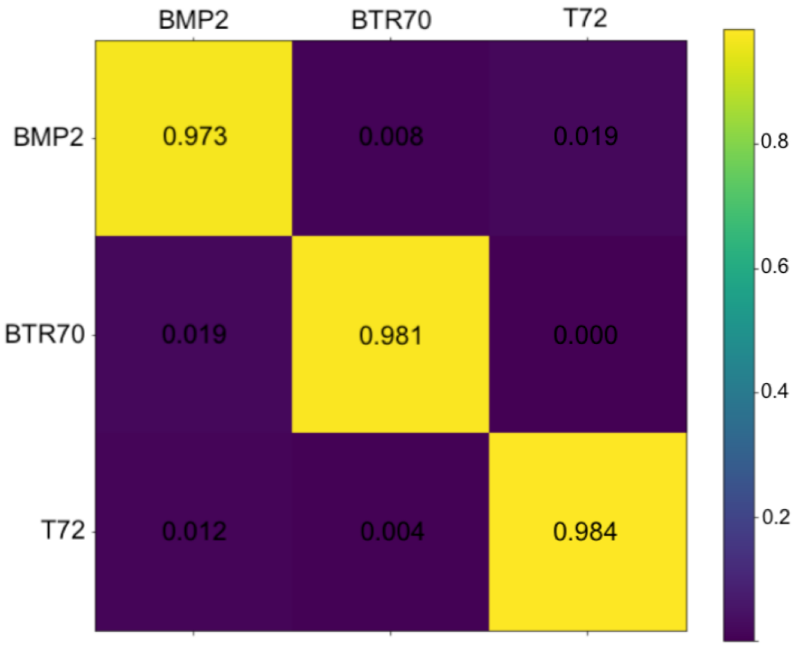
- ML technique using a pre-trained model being re-purposed for another task
- Used when there's insufficient data for the new task
- Improve overall performance or progress
- Using for recognizing SAR imagery

Metrics

- Plotting accuracy
- Confusion matrices
  - Columns represent actual labels, rows represent predicted labels
  - Strong diagonal means things are being predicted well
- Precision
  - $\frac{True\ Positives}{True\ Positives + False\ Positives}$
- Recall
  - $\frac{True\ Positives}{True\ Positives + False\ Negatives}$
- F1-Score
  - Mean of Precision and Recall
- Predictions above 99%, 95%, 90%, 80% 70%

Transfer Learning on MSTAR





Accuracy: 0.979
Loss: 0.078

	Precision	Recall	F1-Score
BMP2	0.97	0.97	0.97
BTR70	0.99	0.98	0.98
T72	0.98	0.98	0.98

> %99.0: 0.9053177691309987
> %95.0: 0.9481193255512321
> %90.0: 0.9610894941634242
> %80.0: 0.980544747081712
> %70.0: 0.9909208819714657

Experimentation

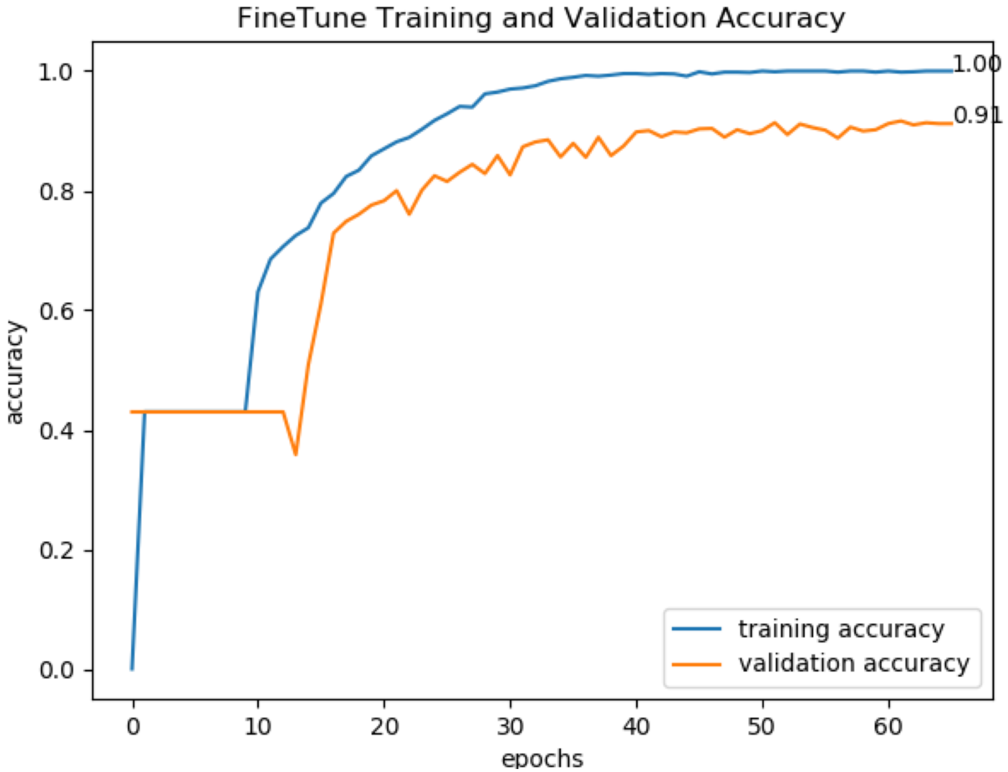
Transfer Learned Model

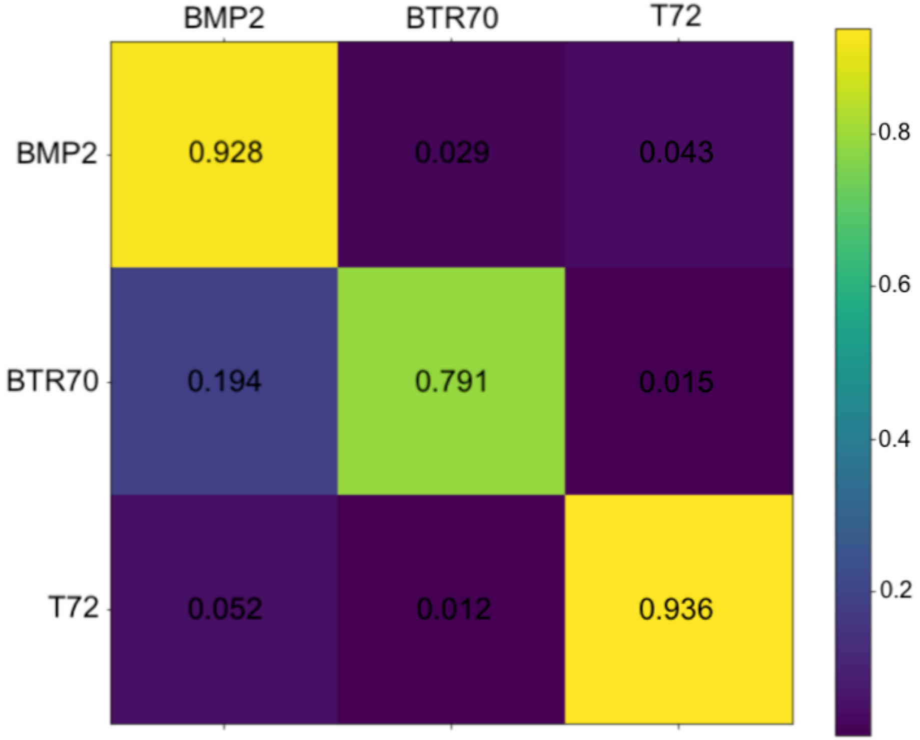
- Fine-Tuning
- Resampling
- Cross Validation

Evaluating TL vs. Standard ML

- ImageNet vs. Random Weights
- Accuracy Curves Transfer Learned on Different Models
    - Random, ImageNet, CIFAR-10, Greyscale CIFAR-10

Fine-tuning





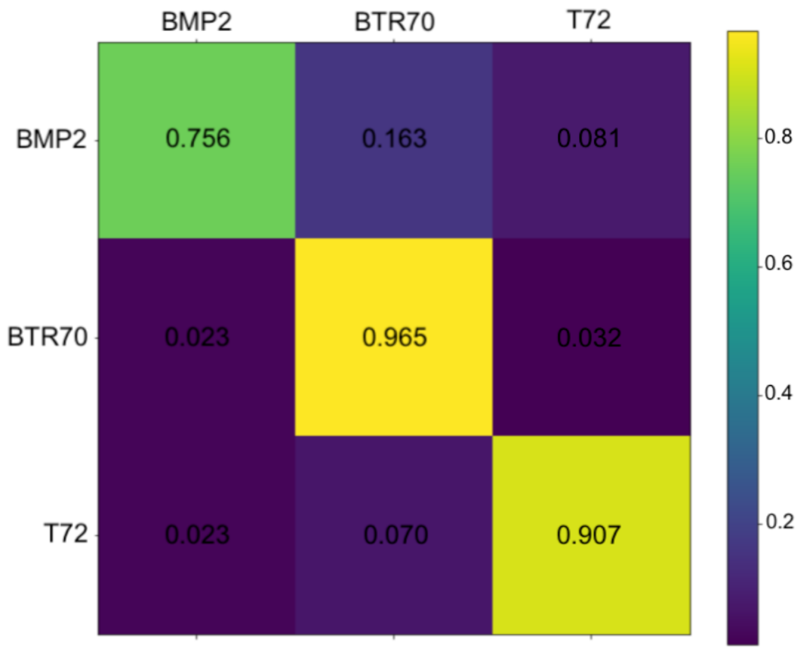
Accuracy: 0.912
Loss: 0.264

	Precision	Recall	F1-Score
BMP2	0.95	0.93	0.95
BTR70	0.93	0.86	0.89
T72	0.94	0.98	0.96

> %99.0: 0.6615384615384615
> %95.0: 0.8029304029304030
> %90.0: 0.8534798534798534
> %80.0: 0.9098901098901099
> %70.0: 0.9472527472527472

Resampling (Under/Over)

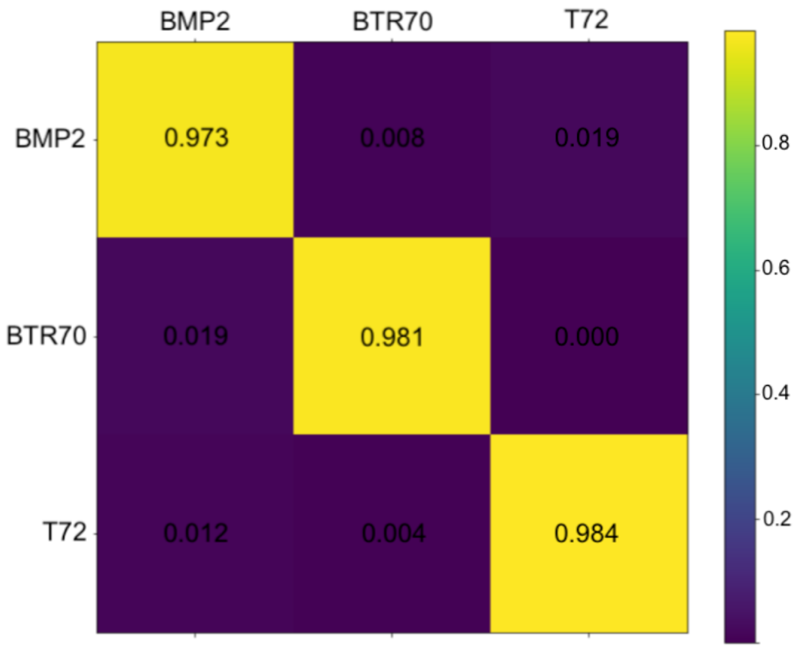
Undersampling



Accuracy: 0.875, Loss: 0.316

	Precision	Recall	F1-Score
BMP2	0.94	0.76	0.84
BTR70	0.81	0.97	0.88
T72	0.91	0.91	0.87

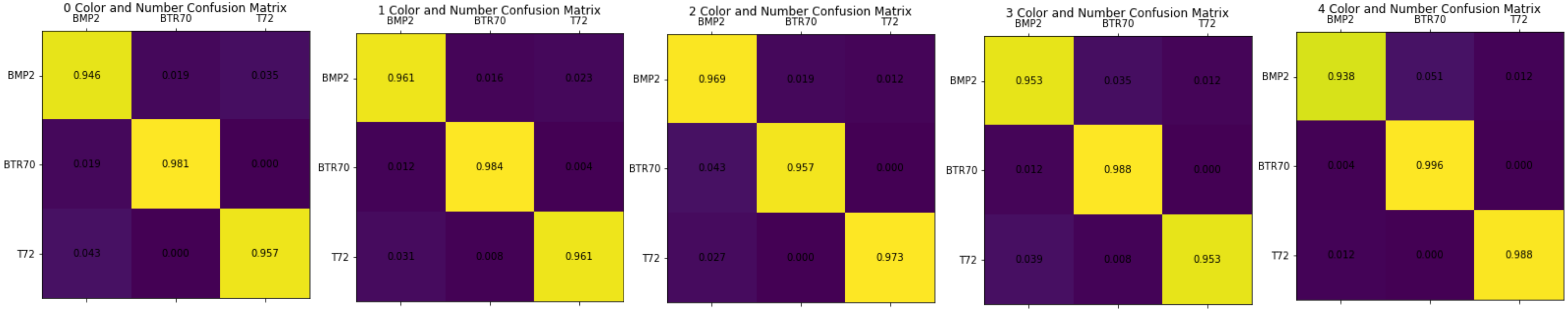
Oversampling



Accuracy: 0.979, Loss: 0.078

	Precision	Recall	F1-Score
BMP2	0.97	0.97	0.97
BTR70	0.99	0.98	0.98
T72	0.98	0.98	0.98

5-Fold Cross Validation



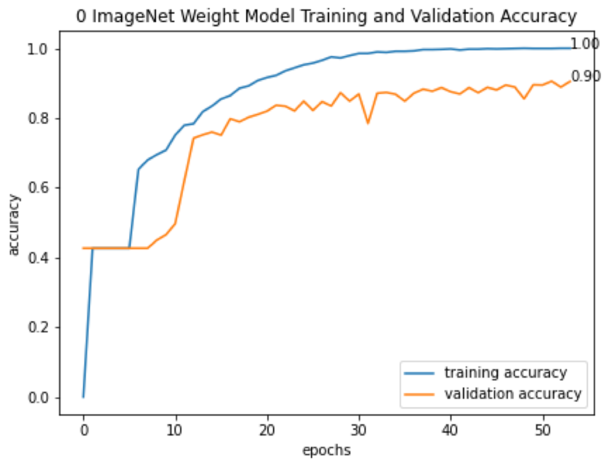
	0	1	2	3	4	Average	StDev
Accuracy	0.96108	0.96887	0.96627	0.96498	0.97405	0.96705	0.00481
Loss	0.13806	0.08896	0.13581	0.10194	0.09145	0.11124	0.02396

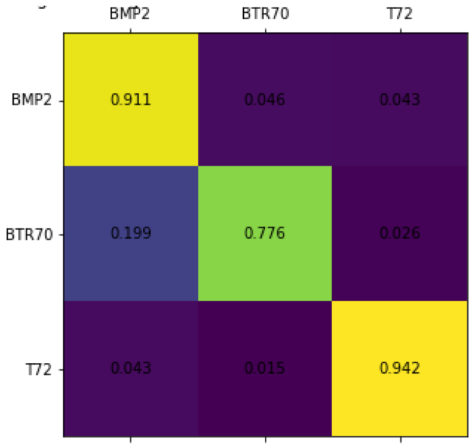
Is ImageNet Helping?

	ImageNet Weights		Random Weights	
	Accuracy	Loss	Accuracy	Loss
0	0.904762	0.275182	0.699634	0.719449
1	0.891575	0.296550	0.703297	0.738245
2	0.901099	0.274274	0.705495	0.719434
3	0.878388	0.319863	0.715751	0.703722
4	0.886447	0.293725	0.731868	0.655388
Average	0.891452	0.292219	0.714652	0.6986042
StDev	0.009909	0.016731	0.014369	0.0352171

ImageNet v. Random Weights

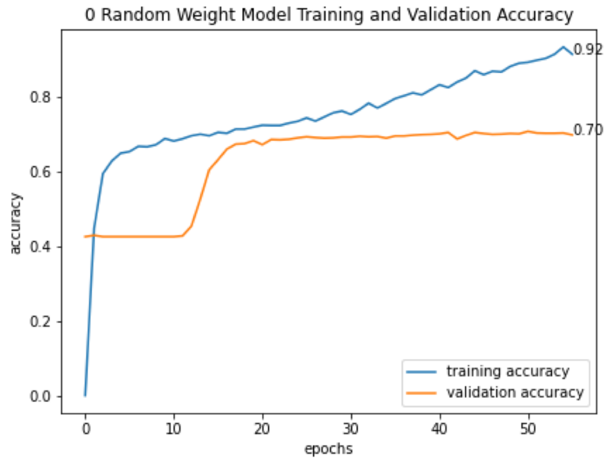
ImageNet Weights

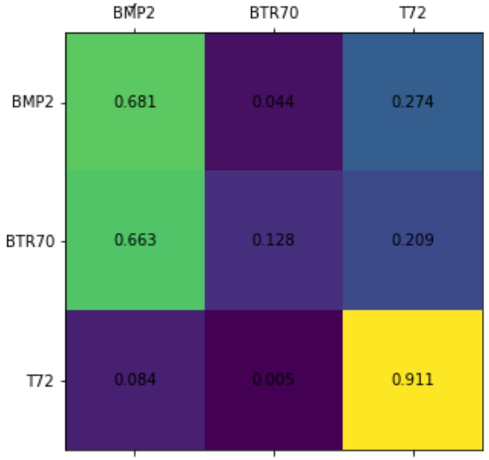




	Precision	Recall	F1-Score
BMP2	0.89	0.91	0.90
BTR70	0.81	0.78	0.79
T72	0.95	0.94	0.94

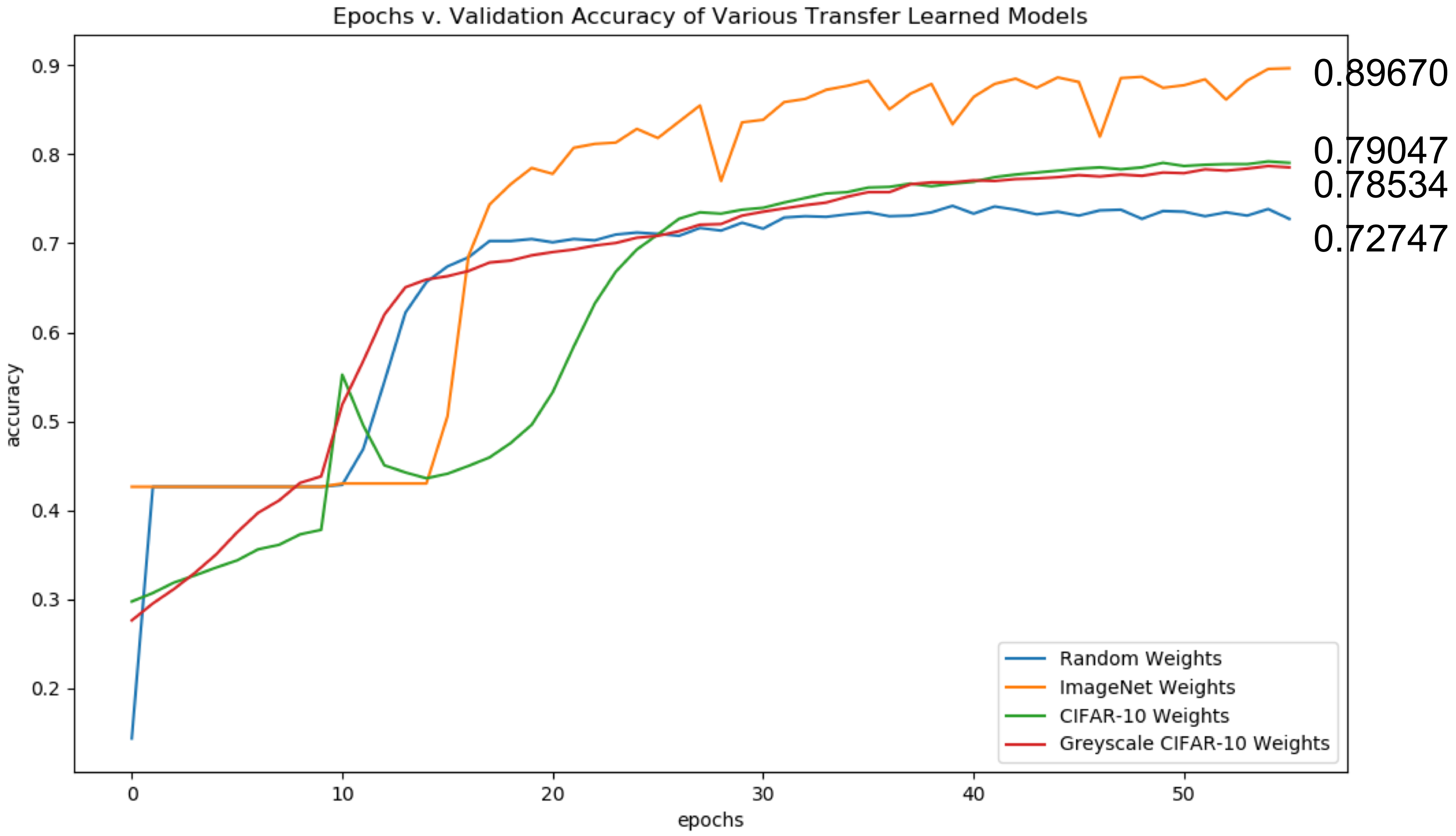
Random Weights





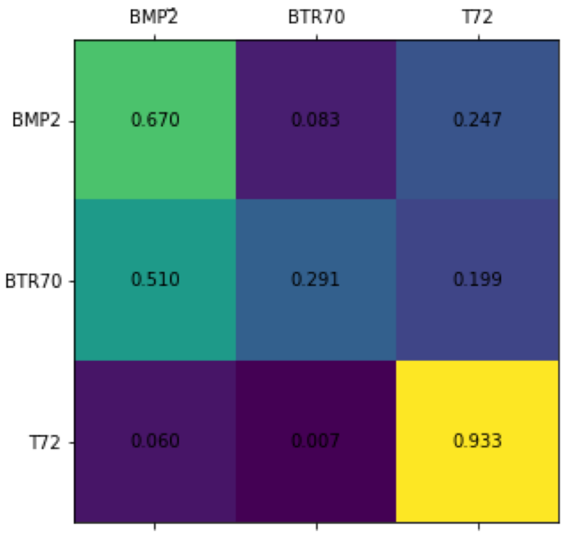
	Precision	Recall	F1-Score
BMP2	0.69	0.68	0.69
BTR70	0.46	0.13	0.20
T72	0.72	0.91	0.81

Accuracies from Different Transfer Learned Models

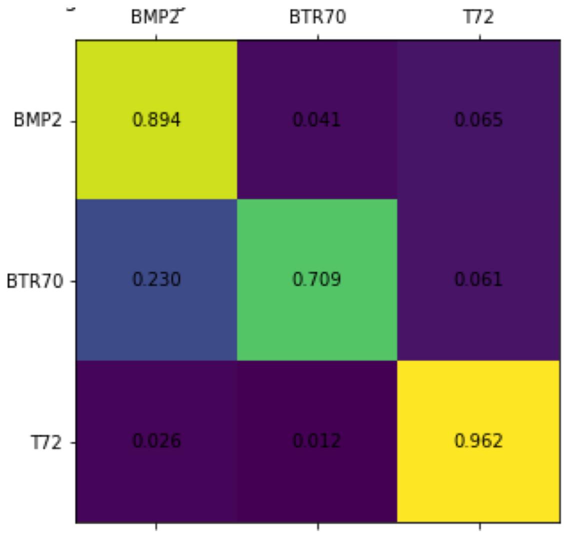


Metrics from Different Transfer Learned Models

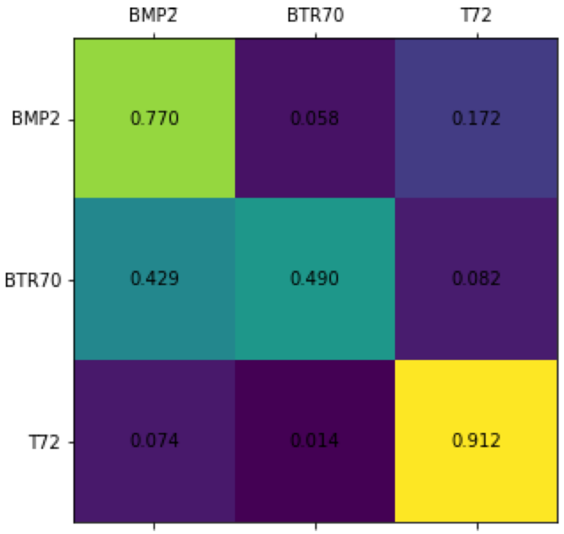
Random Weights



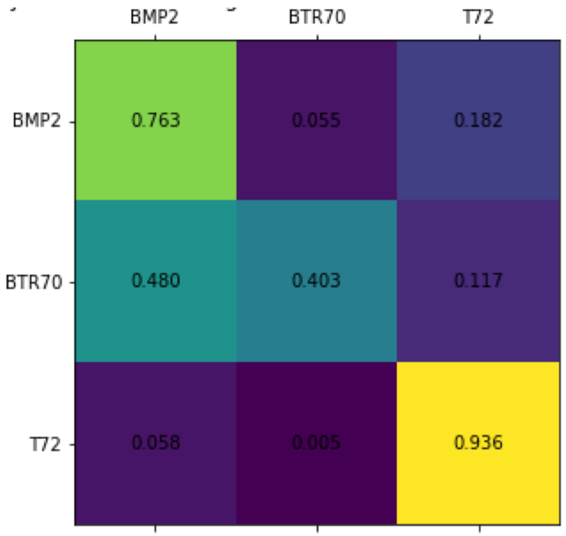
ImageNet Weights



CIFAR-10 Weights



Greyscale Weights



Random Weights

	Precision	Recall	F1-Score
BMP2	0.74	0.67	0.70
BTR70	0.52	0.29	0.37
T72	0.75	0.93	0.83

ImageNet Weights

	Precision	Recall	F1-Score
BMP2	0.90	0.89	0.90
BTR70	0.82	0.71	0.76
T72	0.92	0.96	0.94

CIFAR-10 Weights

	Precision	Recall	F1-Score
BMP2	0.78	0.77	0.78
BTR70	0.70	0.49	0.57
T72	0.82	0.91	0.86

Greyscale Weights

	Precision	Recall	F1-Score
BMP2	0.78	0.76	0.77
BTR70	0.69	0.40	0.51
T72	0.81	0.94	0.87

Wrap Up

Lessons Learned

- ImageNet contains image classification models/datasets for swath/stripmap SAR, but no models specifically for spotlight SAR
- Transfer learning can help improve performance of classifying SAR images

Next Steps

- Test and compare results using more complex datasets (BrightSpark, GOTCHA, classified sets, etc.)
- Look into self-supervised approaches to provide SAR pre-processing
- Leverage this work in support of a JSTARS SAR ML initiative.

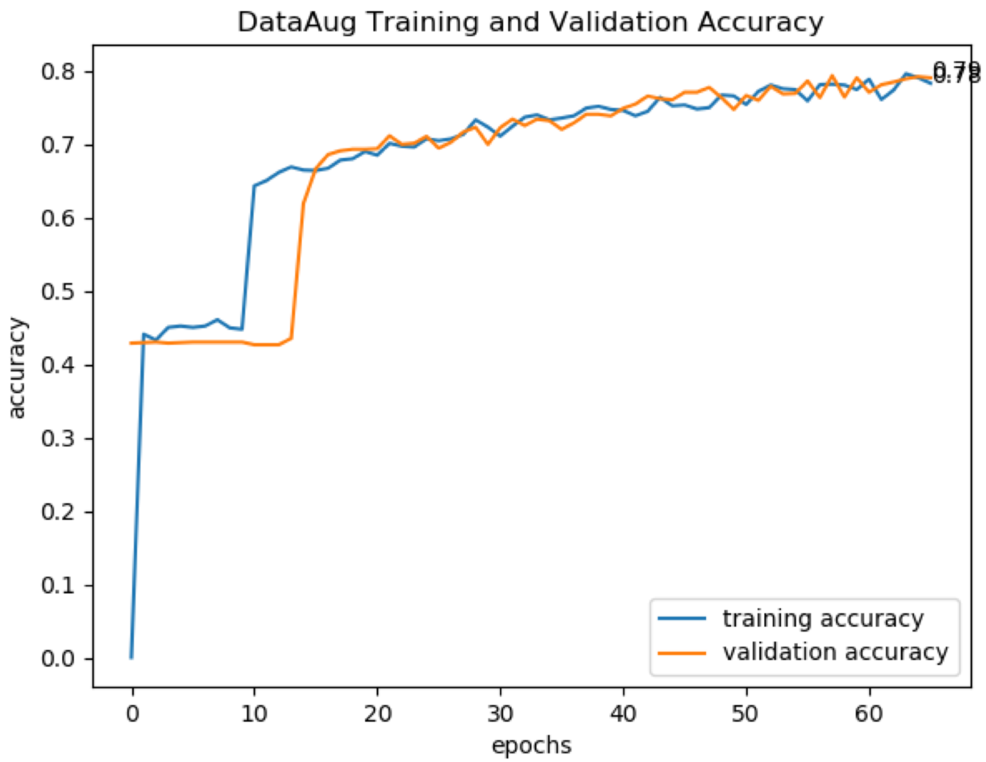
Thanks for listening!
Questions? Comments?

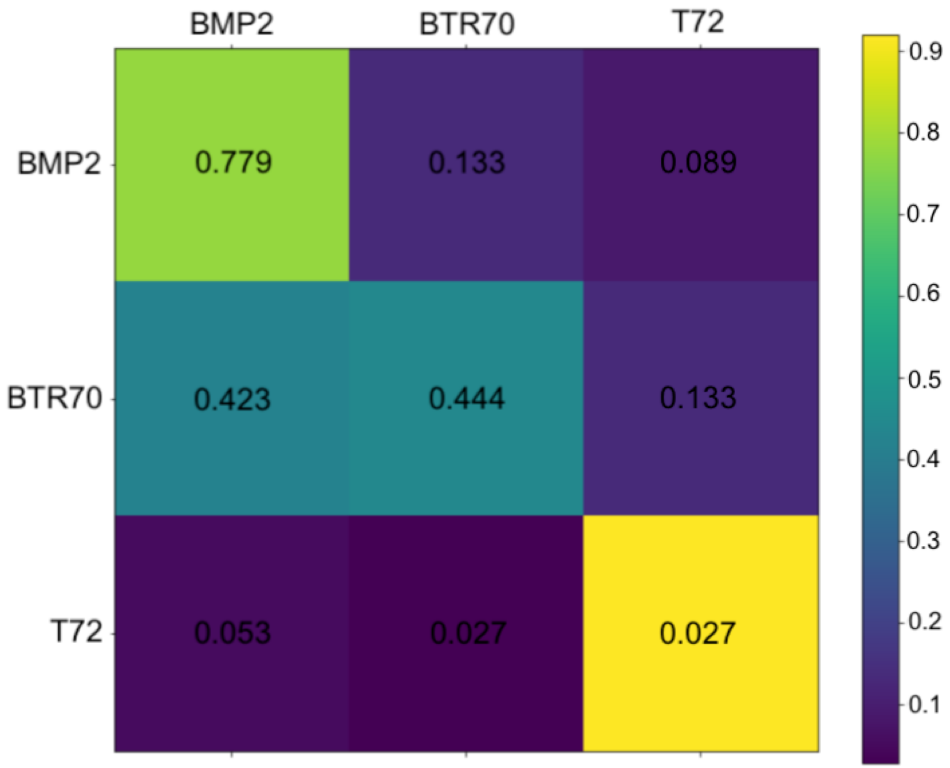
Backup Slides

SAGE Program

- **Develop semi-autonomous software tools that support multi-INT fusion and the multi-domain “phases” of PED**
  - **Implement in, on, and out of the loop capabilities making *faster decisions* in challenging conditions and environments to create *more complete products***
  - **Support for single, multiple, and disaggregated sensor capabilities**
  - **Deliver multi-source fused products for context and assessment**

Data augmentation



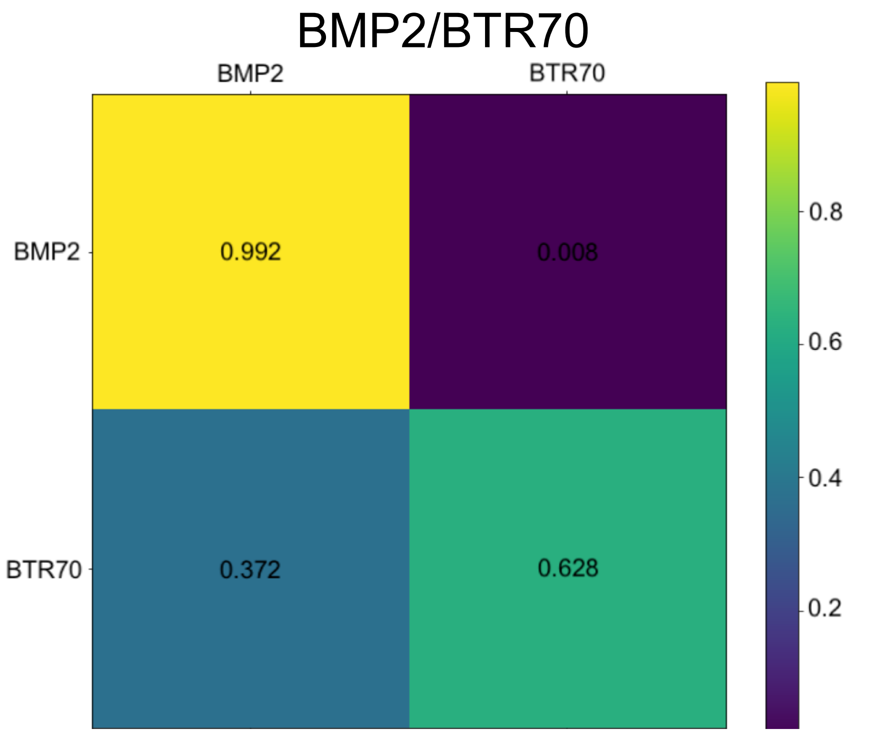


Accuracy: 0.790
Loss: 0.524

	Precision	Recall	F1-Score
BMP2	0.80	0.78	0.79
BTR70	0.48	0.44	0.46
T72	0.87	0.92	0.90

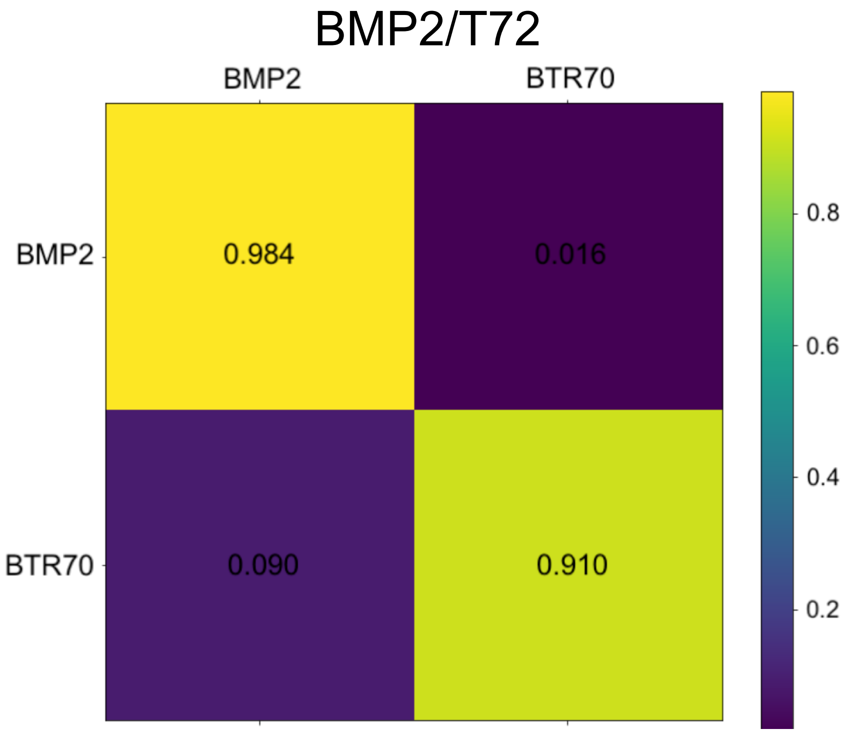
> %99.0: 0.06373626373626373
> %95.0: 0.18095238095238095
> %90.0: 0.26886446886446885
> %80.0: 0.45567765567765567
> %70.0: 0.6175824175824176

Class Sampling (BMP2/BTR70, BMP2/T72)



Accuracy: 0.900, Loss: 0.256

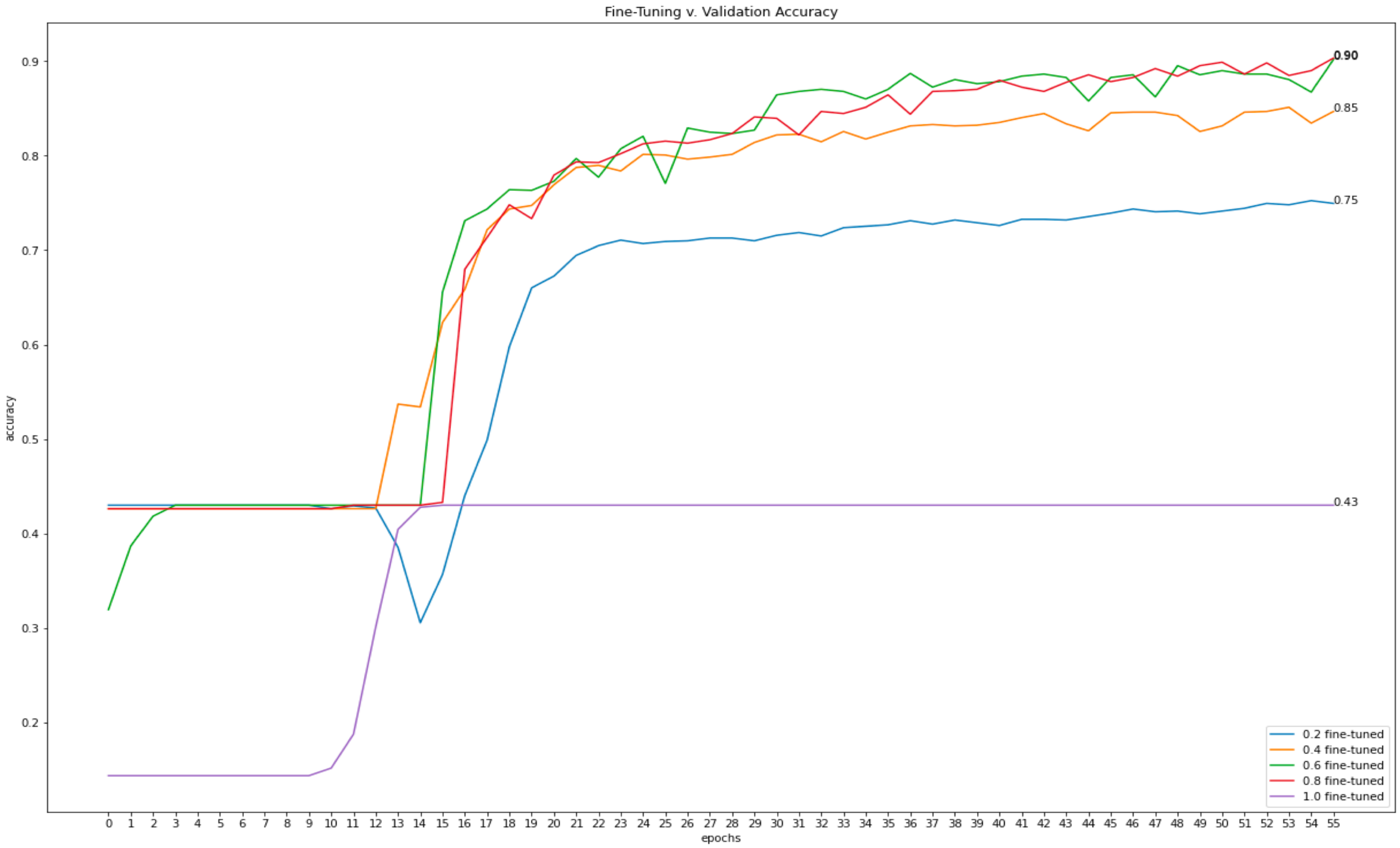
	Precision	Recall	F1-Score
BMP2	0.89	0.99	0.94
BTR70	0.96	0.64	0.76



Accuracy: 0.947, Loss: 0.181

	Precision	Recall	F1-Score
BMP2	0.92	0.98	0.95
T72	0.98	0.91	0.95

Fine-Tuning Different Fractions



of Labels v. Accuracy