Mitigating False Alarms in Infrared-based Precipitation Estimates: A Multi-task Machine Learning Approach

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భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
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A Convolutional Neural Network (CNN) is proposed to address this issue; that is, a multi-task learner integrating two tasks.

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- Follows the traditional approach of classification
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0.6-0.7	68.6%
0.7-0.8	54.3%
0.8-0.9	33.6%
0.9-1	22.6%

Can we use this predicted probability of precipitation to address the False Alarm Ratio?

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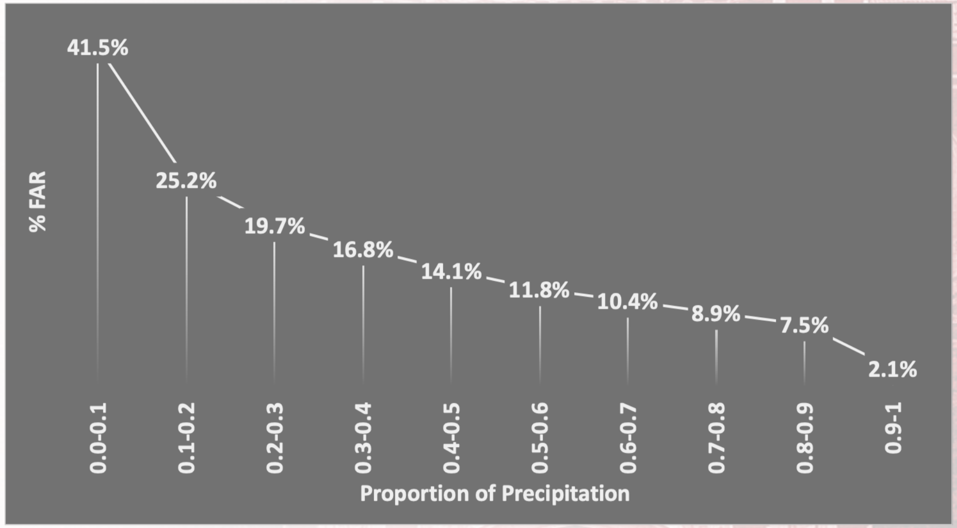
Task 2:

- Formalizes detection as a quantification of the proportion of precipitation within each footprint : Sub-Pixel Variability



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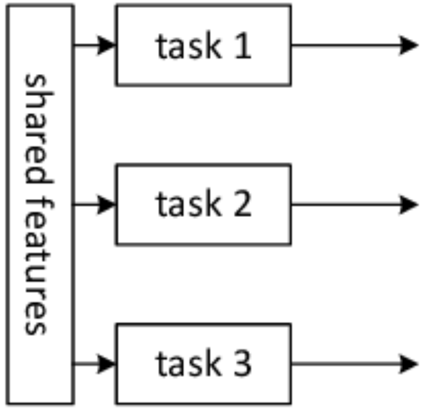
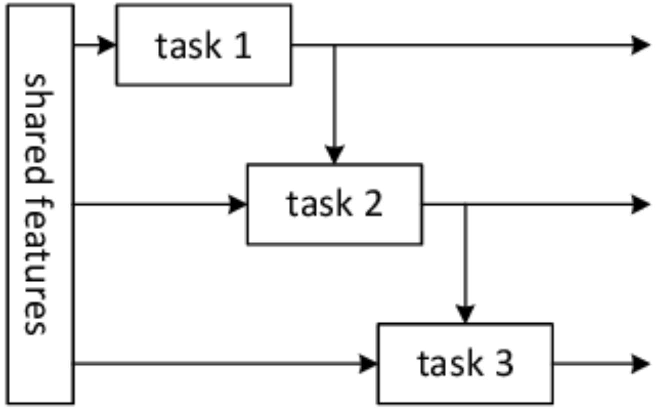
Can we use this sub-pixel variability to identify PoP? Will it help to deal with FAR?

Multi-Task Learning Results

	POD	FAR	HSS
SCaMPR	33.5 %	48.2 %	0.38
Classification	62.4 %	55.6 %	0.48
Classification + Regression: Defining Threshold	62.2 %	52.0 %	0.51
Classification + Regression: Multi-task ML model	64.4 %	52.5 %	0.52



(a) General form of multi-task learning



(b) Multi-task cascade (Dai et al., 2016; CVPR)

Task 1: Proportion of precipitation : Regression
Task 2: Precipitation Detection : Binary Classification
Task 3: Precipitation Quantification

For more results and What is Next?

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Publications

1. Upadhyaya, S., Kirstetter, P. E., Kuligowski, R. J. & Searls, M. (2022). Towards Improved Precipitation Estimation with the GOES-16 Advanced Baseline Imager: Algorithm and Evaluation. Quarterly Journal of the Royal Meteorological Society. https://doi.org/10.1002/qj.4368.
2. Upadhyaya, S. A., Kirstetter, P. E., Kuligowski, R. J., & Searls, M. (2022). Exploring the Temporal Information from GEO Satellites for Estimating Precipitation with Convolutional Neural Networks. IEEE Geoscience and Remote Sensing Letters. https://ieeexplore.ieee.org/document/9819929
3. Upadhyaya, S.A., Kirstetter, P.-E., Kuligowski, R.J., Gourley, J.J. and Grams, H. (2021) Classifying precipitation from GEO Satellite Observations: Prognostic Model. Quarterly Journal of the Royal Meteorological Society. https://doi.org/10.1002/qj.4134.
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5. Upadhyaya, S. A., Kirstetter, P. E., Gourley, J. J., & Kuligowski, R. J. (2020). On the propagation of satellite precipitation estimation errors: From passive microwave to infrared estimates. *Journal of hydrometeorology*, *21*(6), 1367-1381. https://doi.org/10.1175/JHM-D-19-0293.1

Thank You