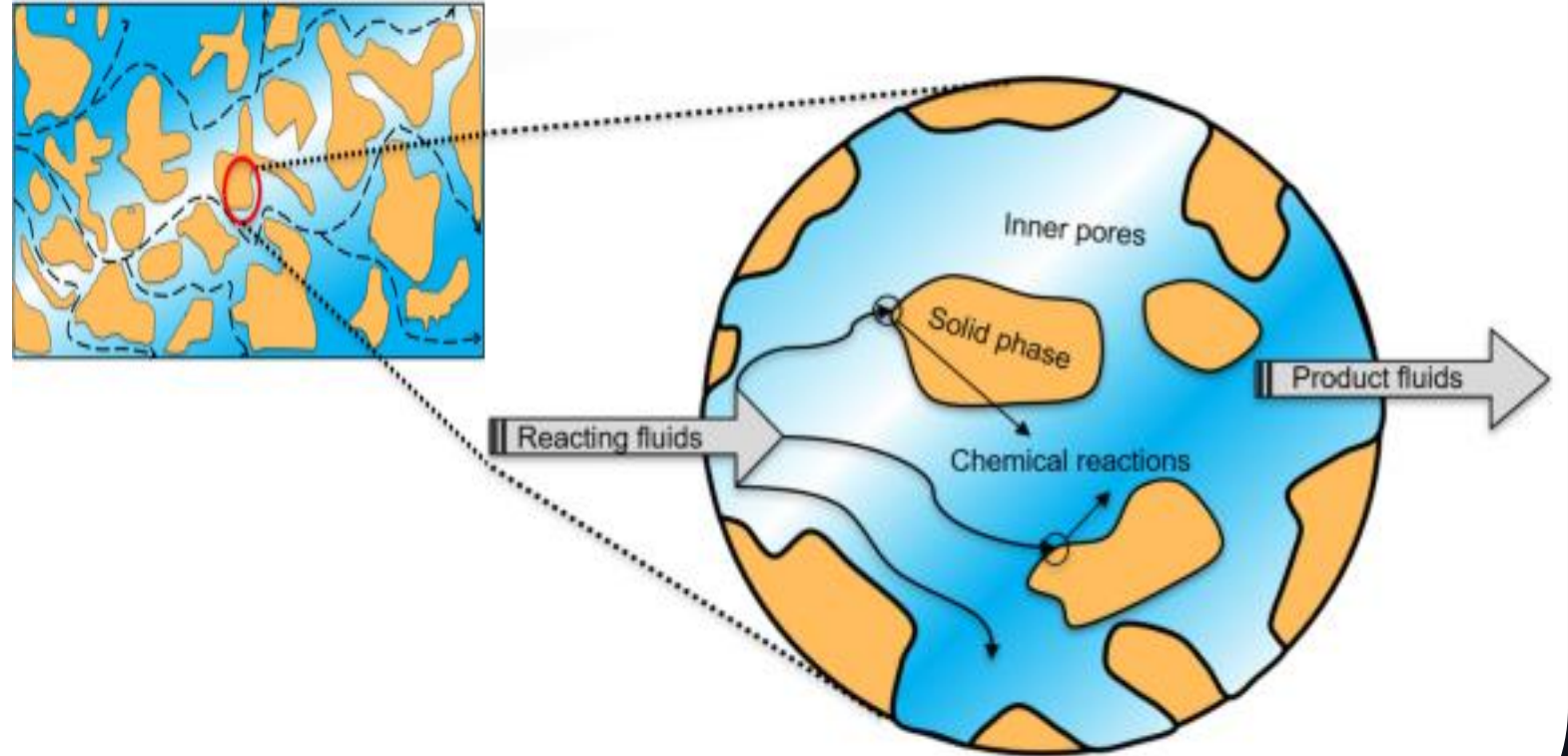


# Machine/Deep Learning Methods for Pore-Mineral Characterization and Surface Areas Analysis.

**Parisa Asadi & Lauren E. Beckingham**  
Department of Civil and Environmental Engineering  
Auburn University

# Introduction

- Acidification and contamination via trace element mobilization [1-5] threaten groundwater.
- Reactions can **alter formation and caprock properties** and may **increase fracture or formation permeability**.



<https://link.springer.com/article/10.1007/s42452-021-04396-9>

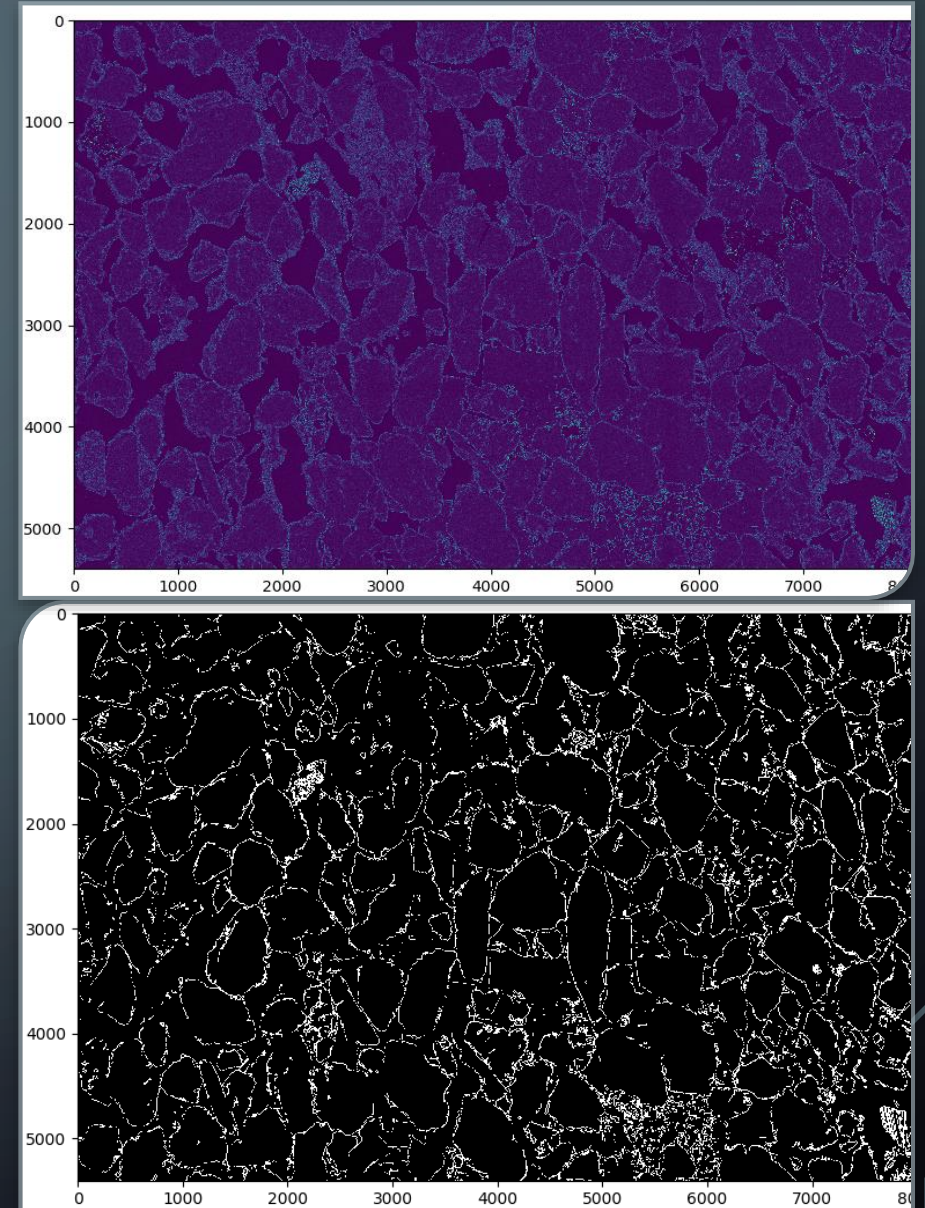


# Why Imaging and Machine Learning Techniques

- Imaging is a powerful technique for mineral segmentation and sample characterization.
  - ✓ time-consuming
  - ✓ labor-intensive
  - ✓ subjective
- It can consider several extracted features at the same time.

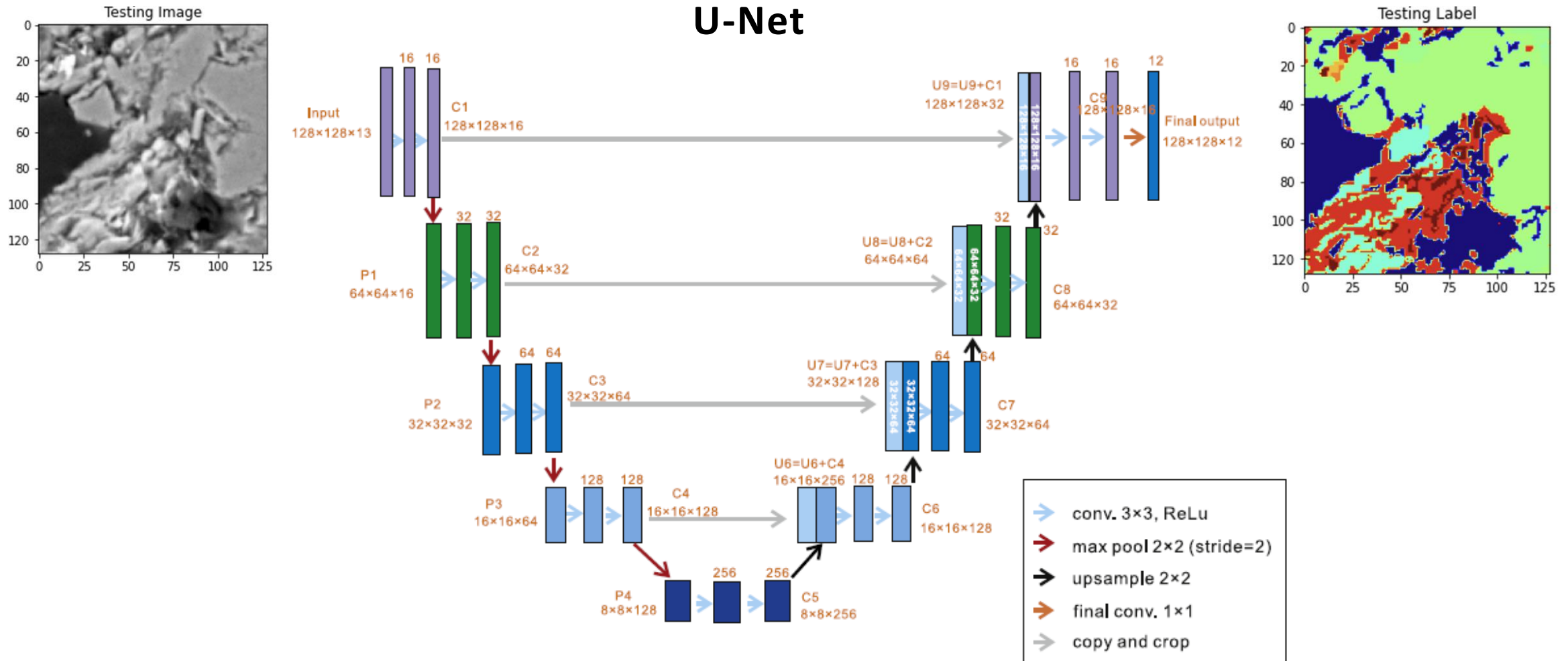
## Objective

- ✓ This study evaluates the performance of machine learning for mineral characterization and surface areas analysis of sandstone samples in various 2D image resolutions.

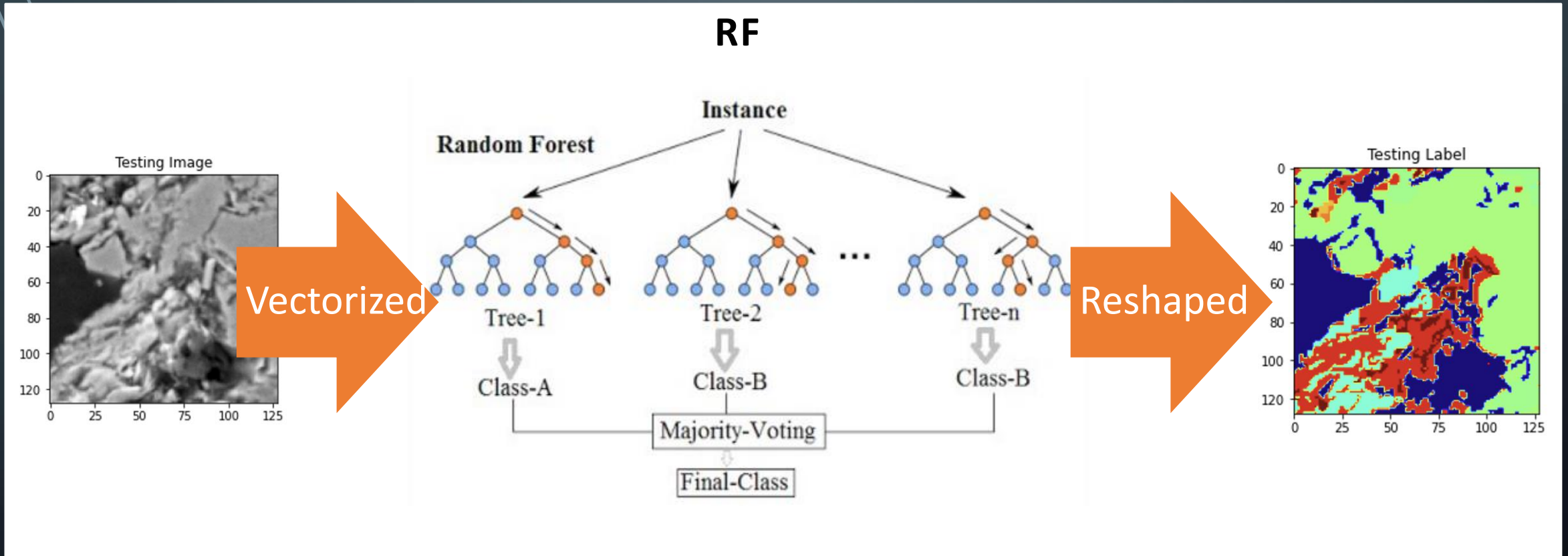


# U-Net Deep Learning Method

## U-Net

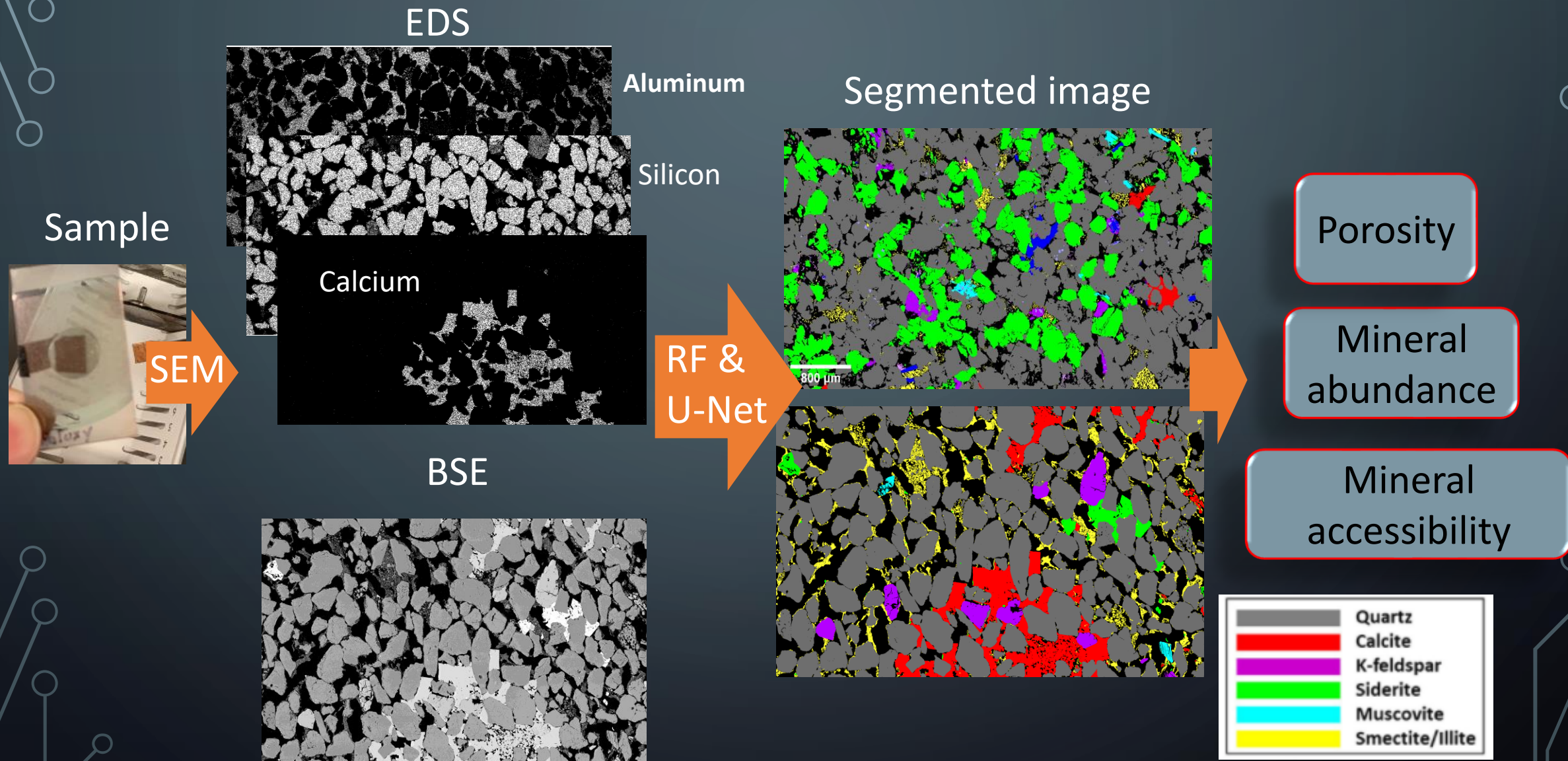


# Random Forest Machine Learning Method





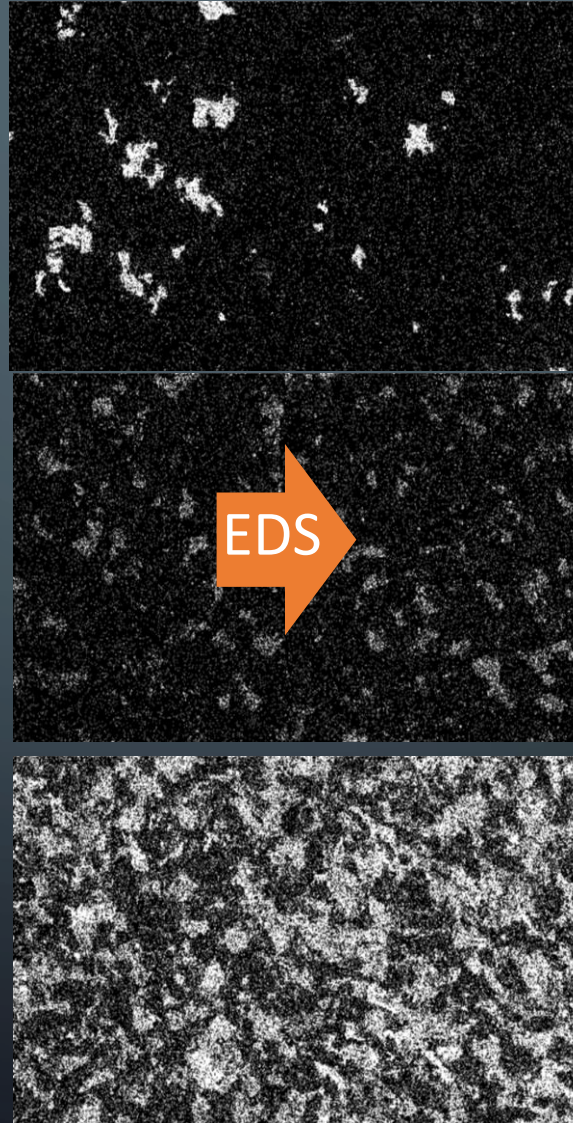
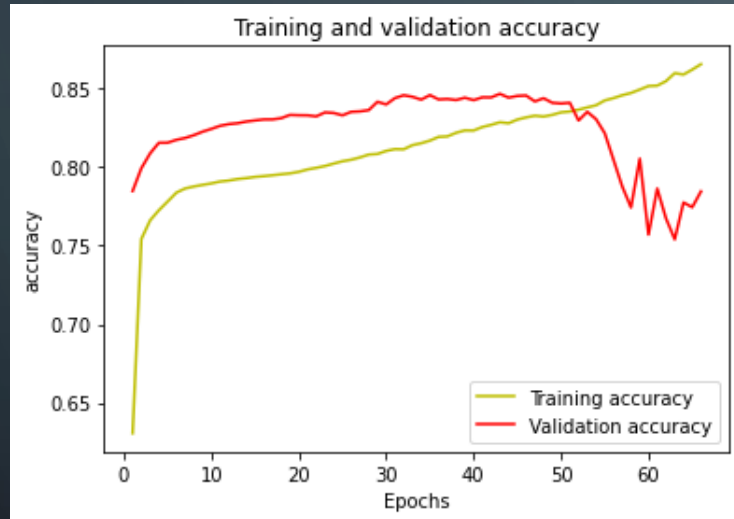
# Workflow of The Study



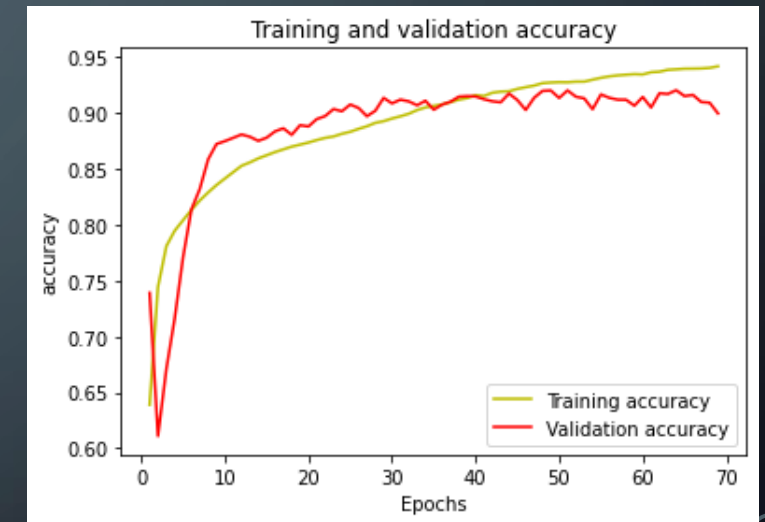
# Results and Discussion

EDS elemental maps provided reliable features to segment different minerals and the model could recognize them.

## BSE

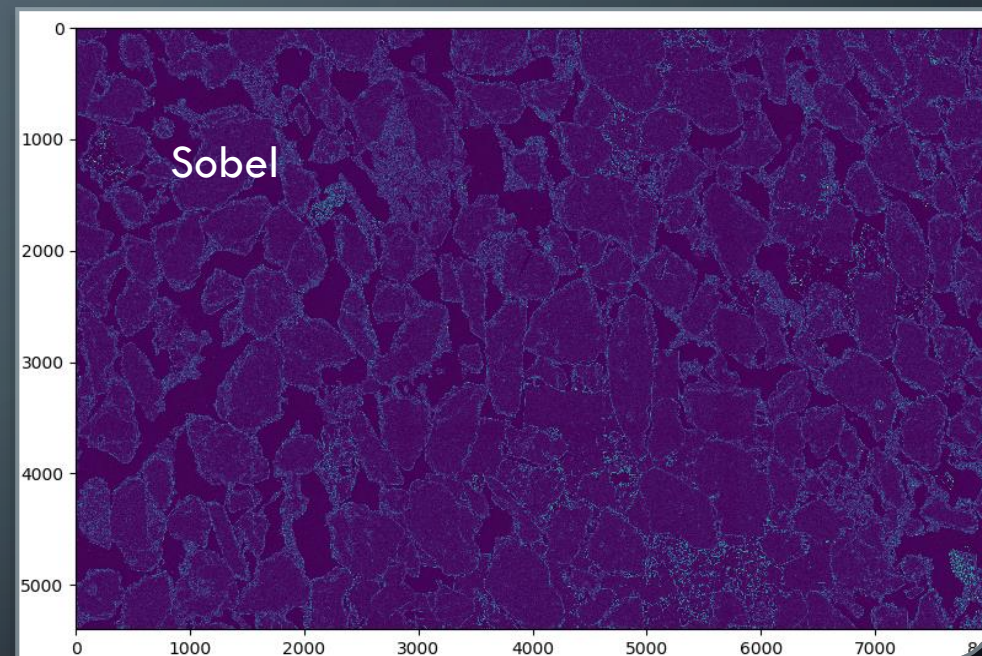
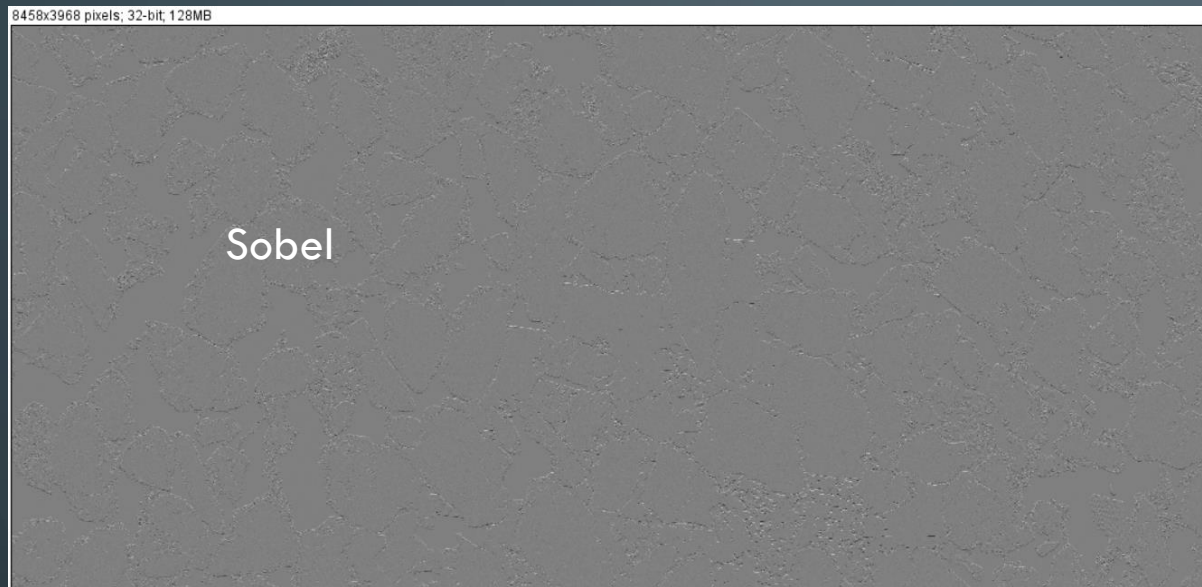


## BSE & EDS





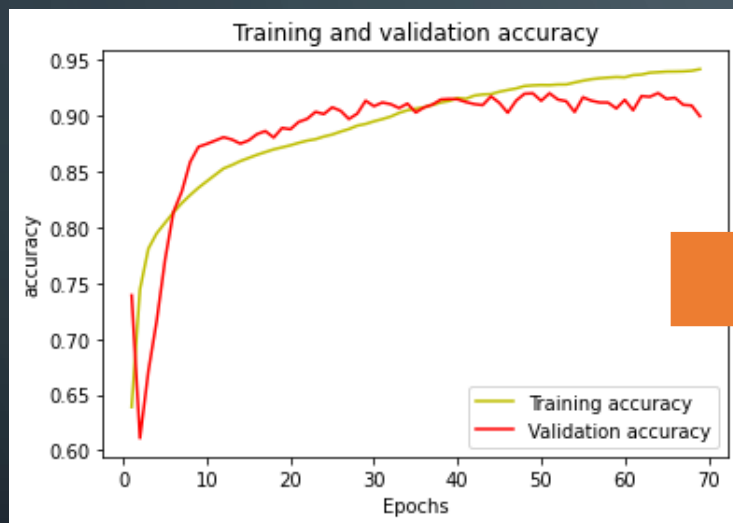
# Filters Add More Features.



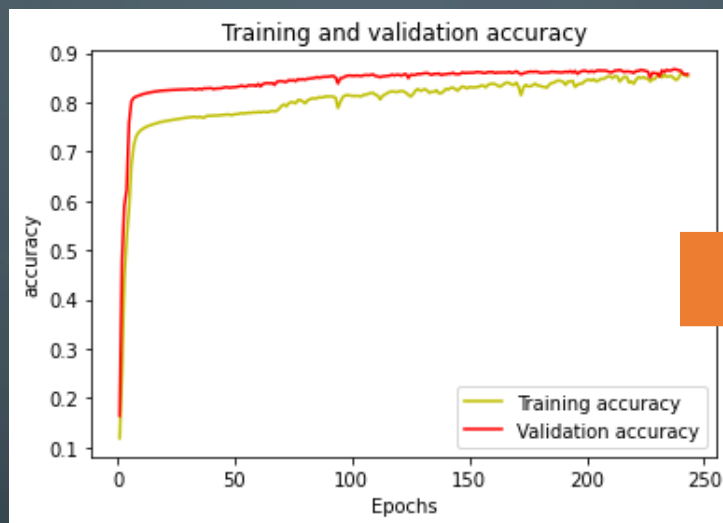


# Results improved by considering both elemental and filter extracted features.

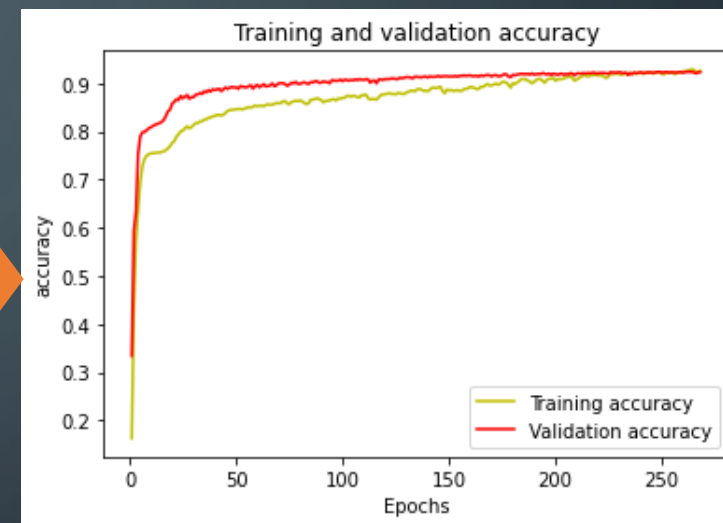
## BSE & EDS



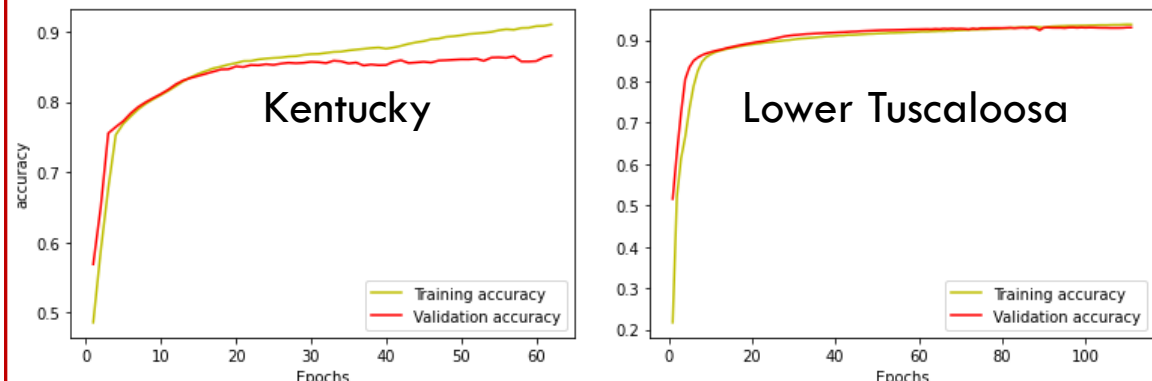
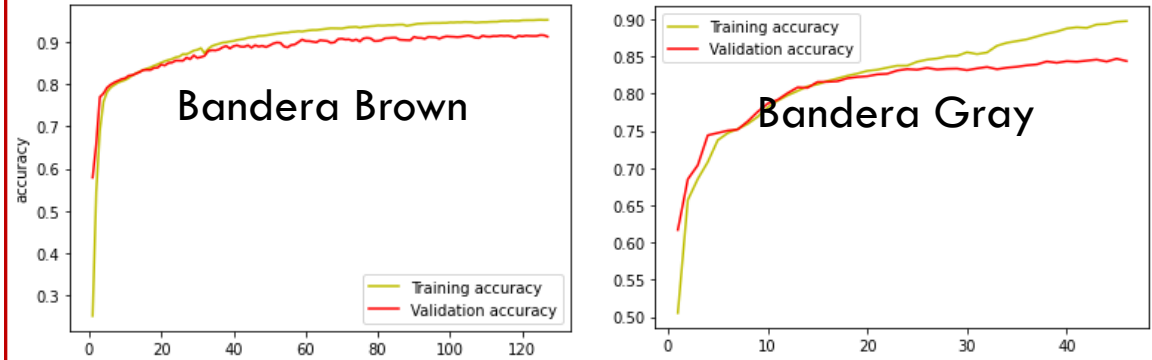
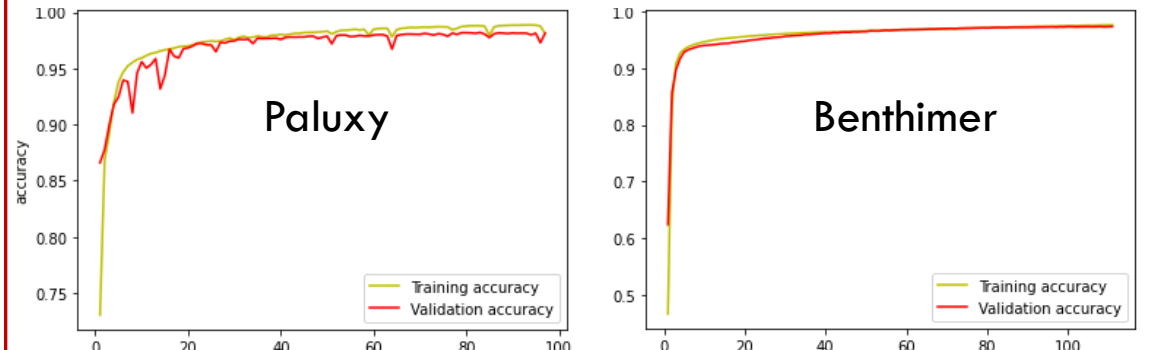
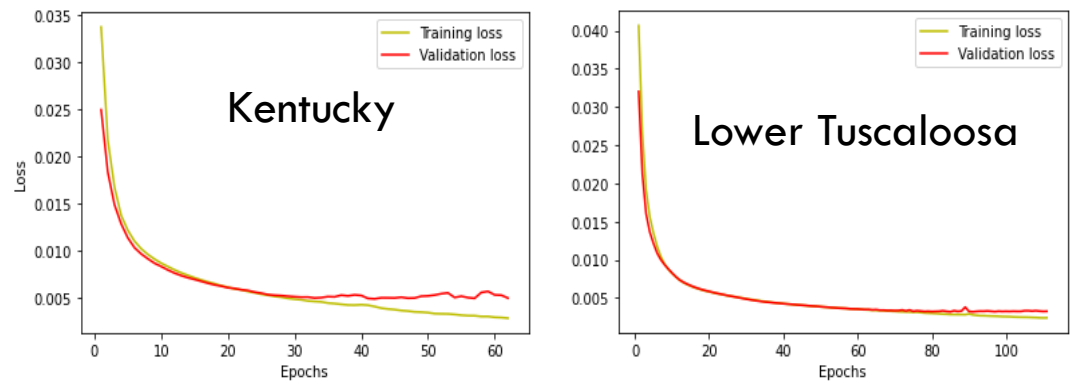
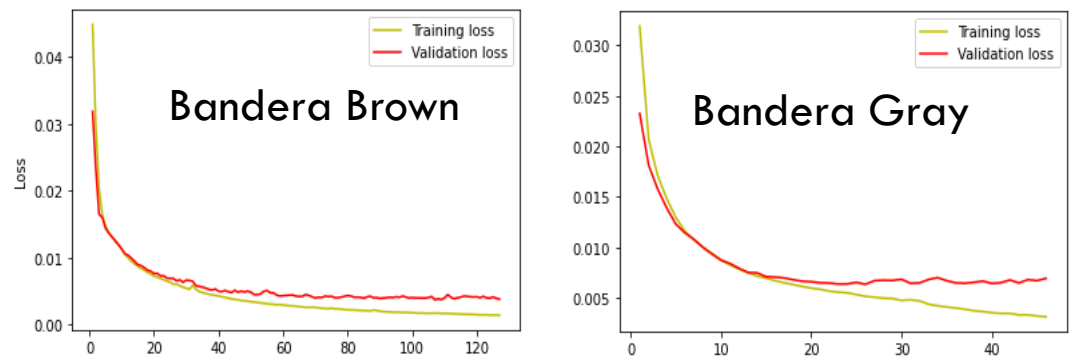
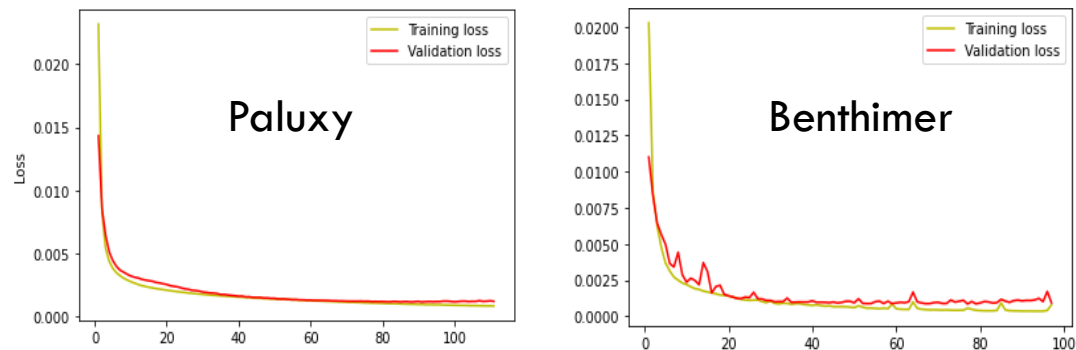
## BSE & Filters



## BSE & EDS & Filters



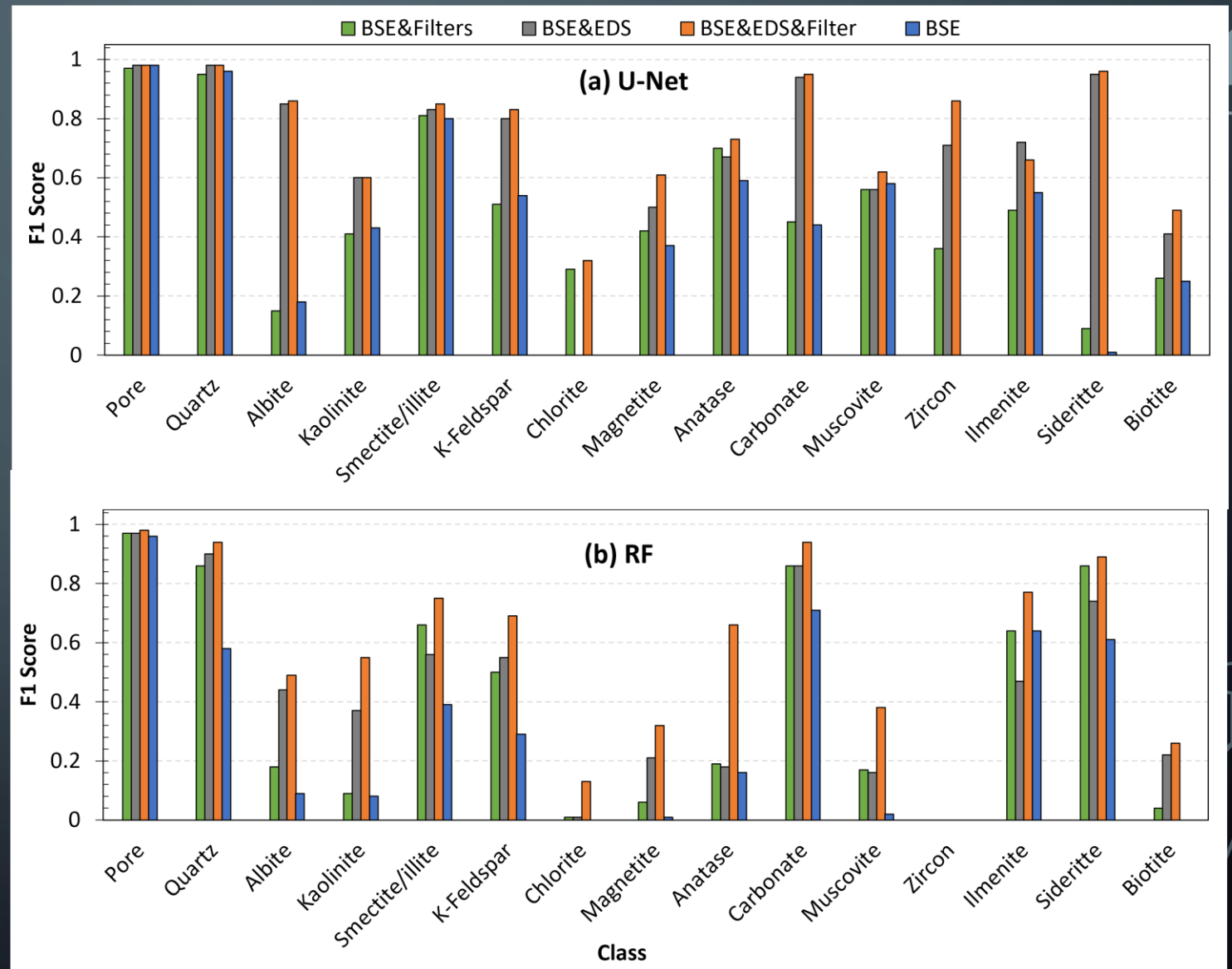
# Convergence Loss and Accuracy Curves Along Iteration





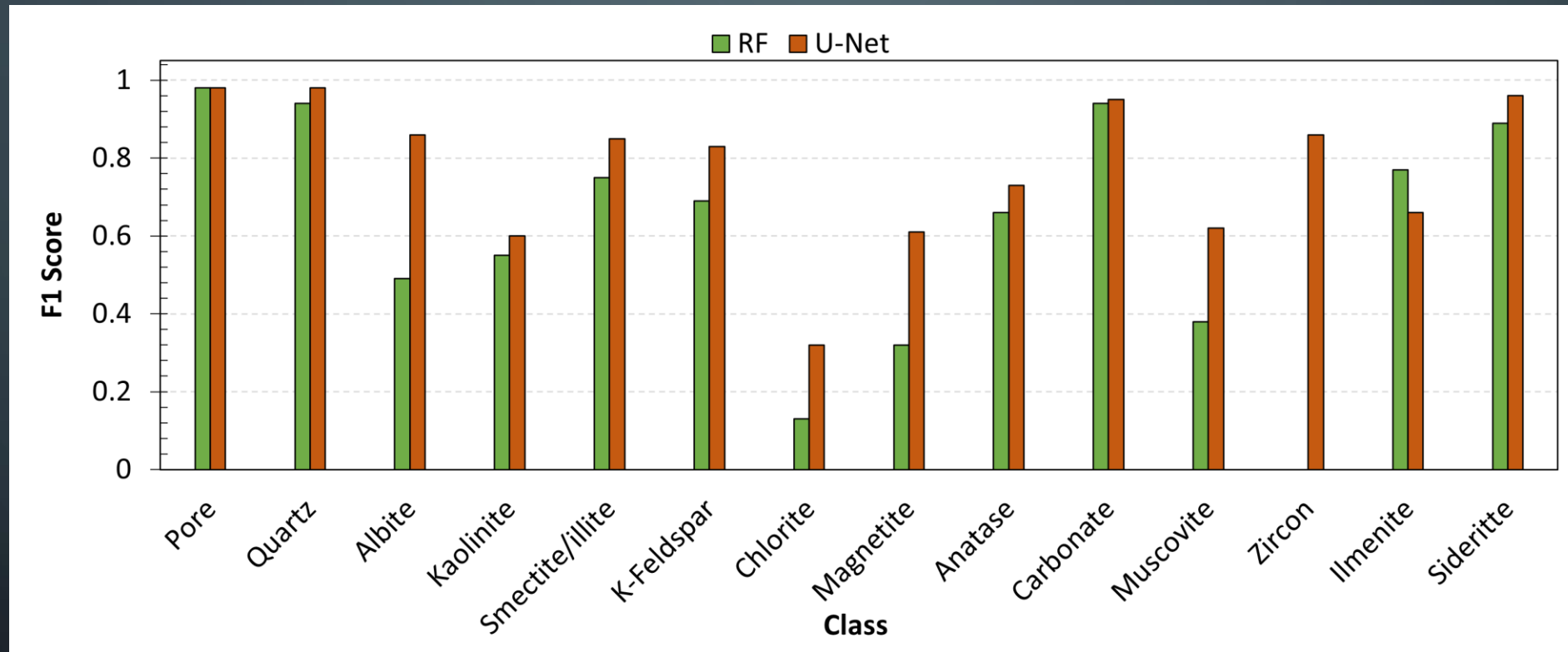
# Performance of Models for Mineral Classification

Both methods had better performance when considering both EDS and filtered images.



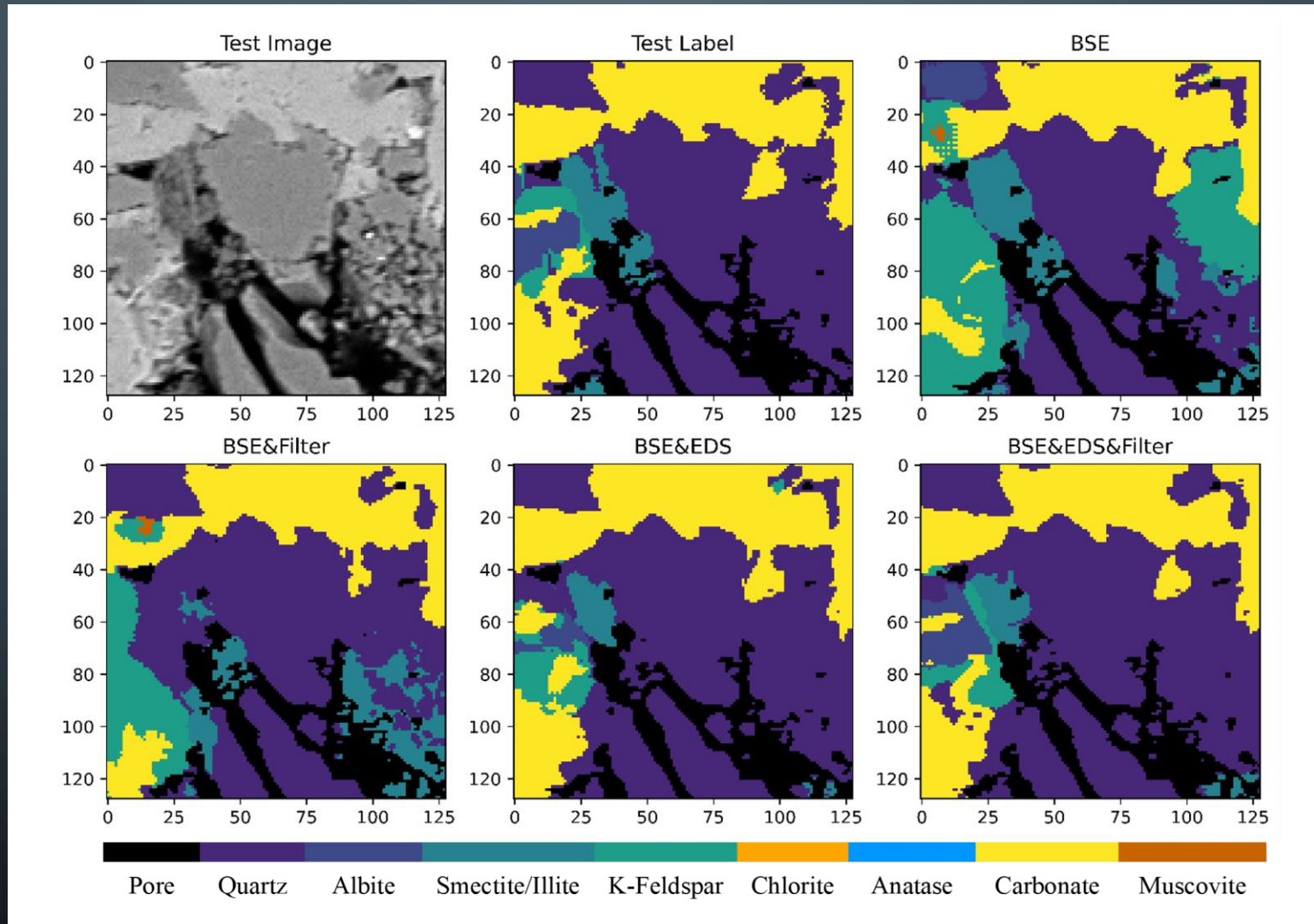
# Comparison of RF and U-Net Performance

U-Net had better results for all minerals.

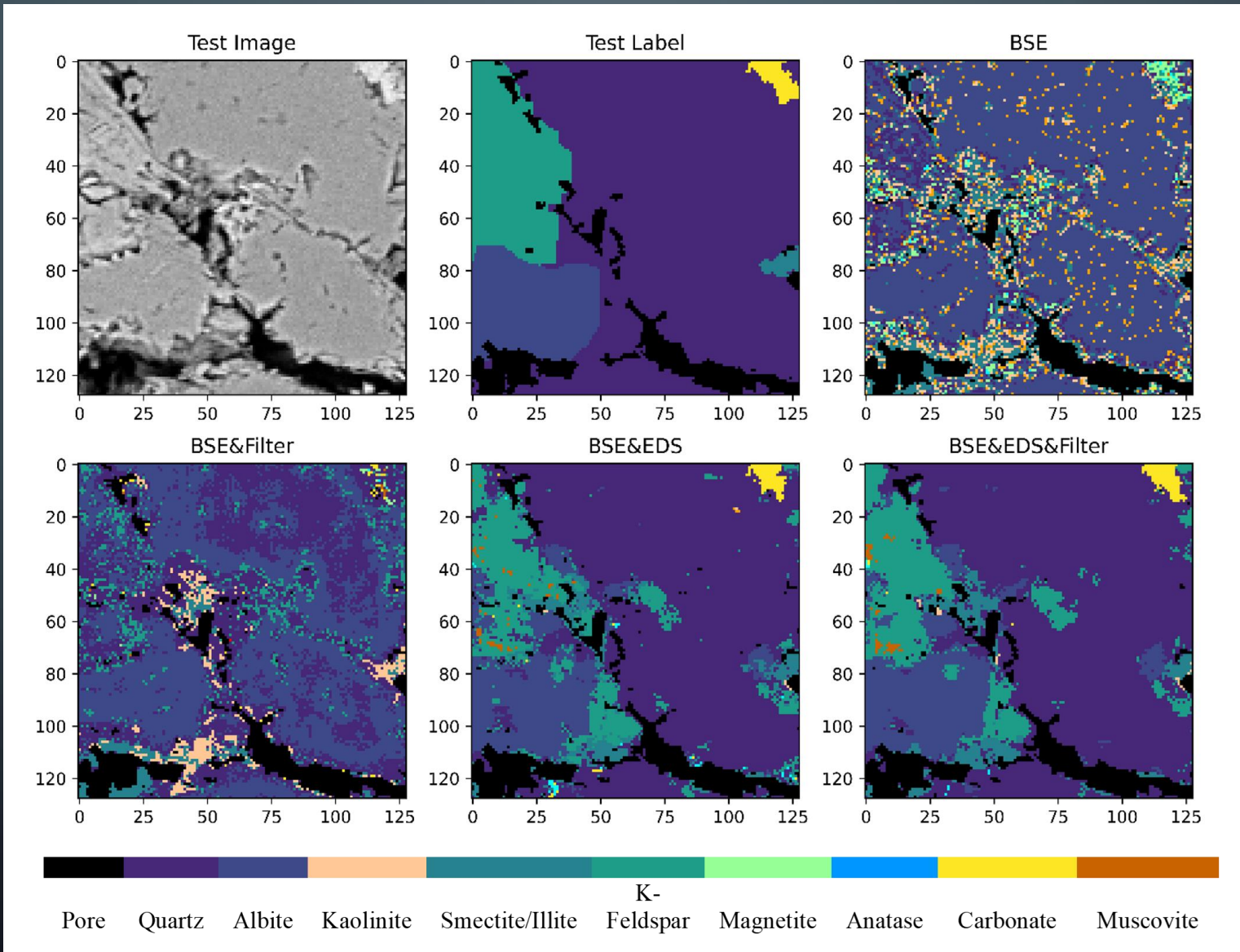




# U-Net Predicted Results On Unseen Sample



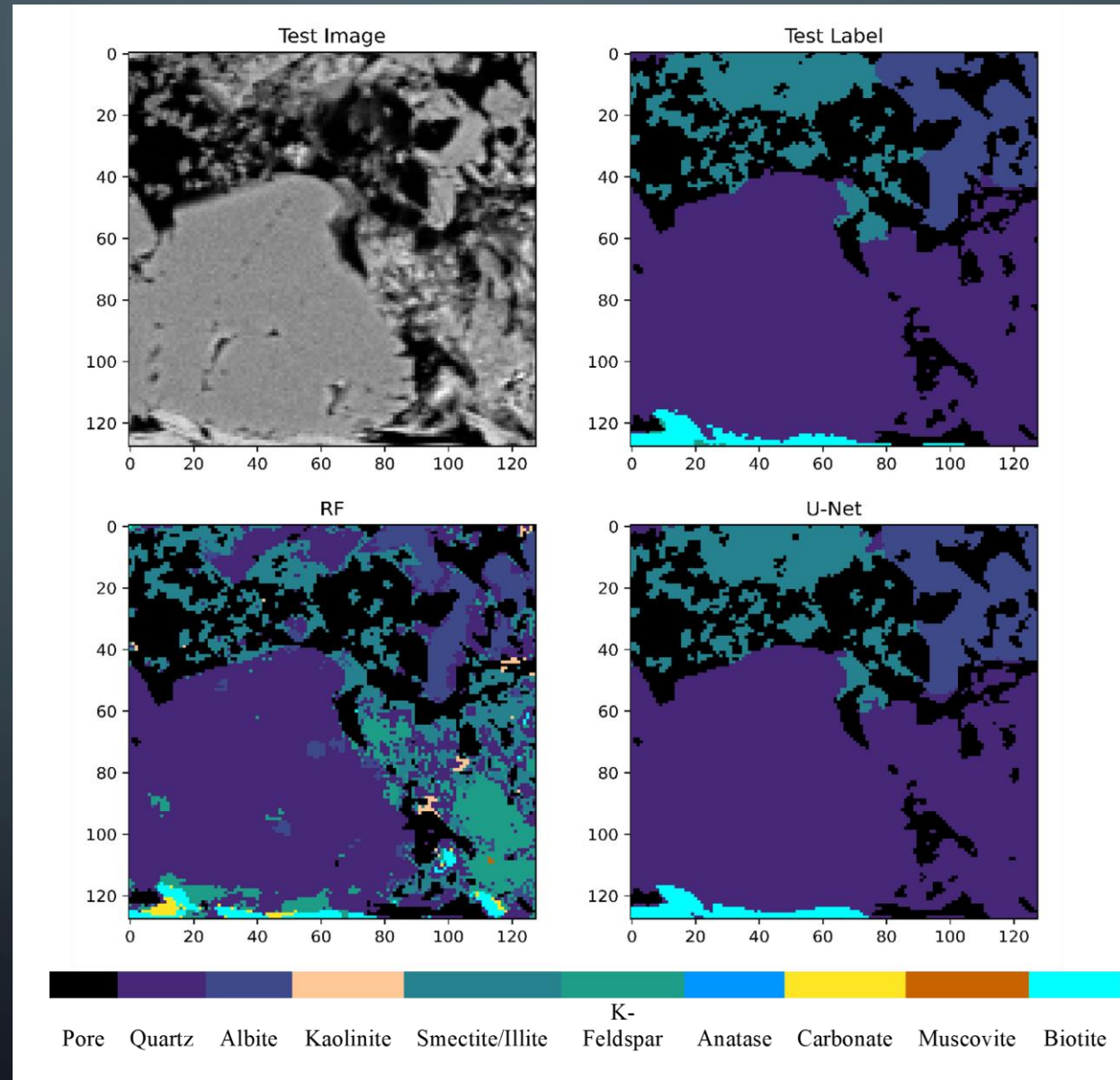
# RF Predicted Results On Unseen Sample





# Predicted Results On Unseen Sample

U-Net had better performance with less noise.



# Predicted Accessibility and Abundance.

Mineral	Chemical formula	Method	Abundance (%)	Accessibility (%)
Quartz	SiO <sub>2</sub>	ground truth	76.83	57.61
		RF	72.62	44.79
		U-Net	77.72	55.86
Kaolinite	Al <sub>2</sub> Si <sub>2</sub> O <sub>5</sub> (OH) <sub>4</sub>	ground truth	0.39	4.85
		RF	0.64	7.18
		U-Net	0.27	3.25
Carbonate	CaCO <sub>3</sub> /MgCO <sub>3</sub> ·CaCO <sub>3</sub>	ground truth	8.47	3.45
		RF	8.35	2.96
		U-Net	6.76	2.46
K-feldspar	KAlSi <sub>3</sub> O <sub>8</sub>	ground truth	3.86	3.30
		RF	4.12	2.07
		U-Net	4.82	3.98



# Conclusion

- Both RF and U-Net models had good performance for predicting quartz (**majority**) abundance and accessibility.
- U-Net achieved a better performance in predicting minority classes such as chlorite and carbonate.
- Similar performance was observed in all models, showing the robustness of the proposed framework.
- The obtained parameters can be utilized to inform reactive transport simulations.

# Acknowledgments & Reference



- This material is based upon work supported by the National Science Foundation under Grant No: 1847243

1. Choi, B. Y. (2019). Potential impact of leaking CO<sub>2</sub> gas and CO<sub>2</sub>-rich fluids on shallow groundwater quality in the Chungcheong region (South Korea): A hydrogeochemical approach. *International Journal of Greenhouse Gas Control*, 84. <https://doi.org/10.1016/j.ijggc.2019.03.010>
2. Qafoku, N. P., Lawter, A. R., Bacon, D. H., Zheng, L., Kyle, J., & Brown, C. F. (2017). Review of the impacts of leaking CO<sub>2</sub> gas and brine on groundwater quality. In *Earth-Science Reviews* (Vol. 169). <https://doi.org/10.1016/j.earscirev.2017.04.010>
3. Apps, J. A., Zheng, L., Zhang, Y., Xu, T., & Birkholzer, J. T. (2010). Evaluation of potential changes in groundwater quality in response to CO<sub>2</sub> leakage from deep geologic storage. *Transport in Porous Media*, 82(1). <https://doi.org/10.1007/s11242-009-9509-8>
4. de Orte, M. R., Sarmiento, A. M., Basallote, M. D., Rodríguez-Romero, A., Riba, I., & delValls, A. (2014). Effects on the mobility of metals from acidification caused by possible CO<sub>2</sub> leakage from sub-seabed geological formations. *Science of the Total Environment*, 470–471. <https://doi.org/10.1016/j.scitotenv.2013.09.095>
5. Qin, F., & Beckingham, L. E. (2021). The impact of mineral reactive surface area variation on simulated mineral reactions and reaction rates. *Applied Geochemistry*, 124, 104852.



The background is a dark blue gradient with a large, faint circular pattern in the center. In the four corners, there are white line-art designs resembling circuit boards or neural networks, with lines and small circles connecting them.

# THANK YOU

PZA0029@AUBURN.EDU