

Sigma Clast Recognition using Transfer Learning with a Convolutional Neural Network



Joseph Robinson, Catherine Meyer, Dr. Gurman Gill
Sonoma State University Computer Science Department



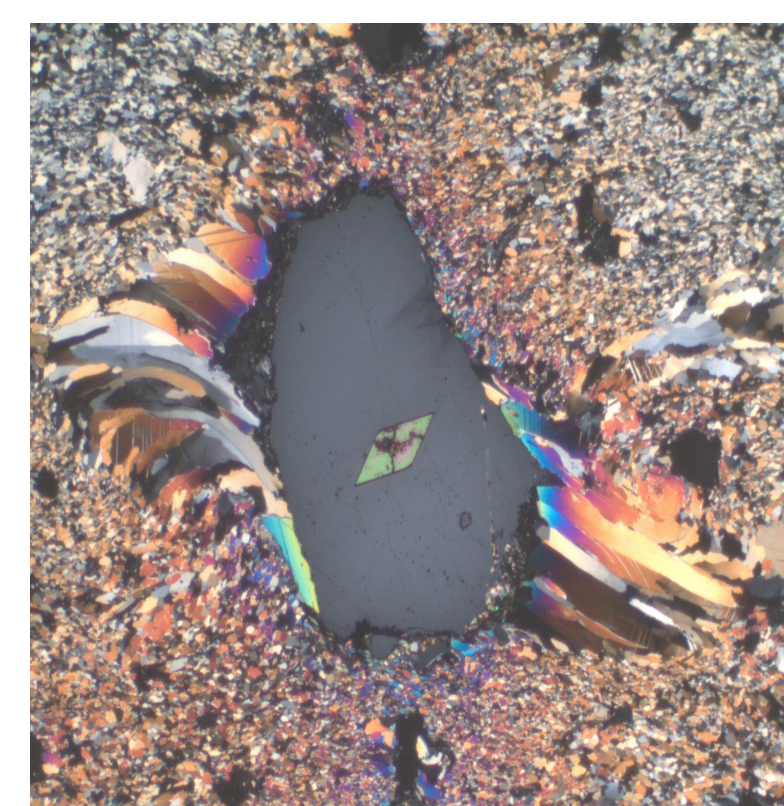
Introduction

- High demand for cyber-infrastructure which enables geological image data to be shared.
- Develop a system which accurately identifies whether an input image contains a sigma-clast, even with limited data.

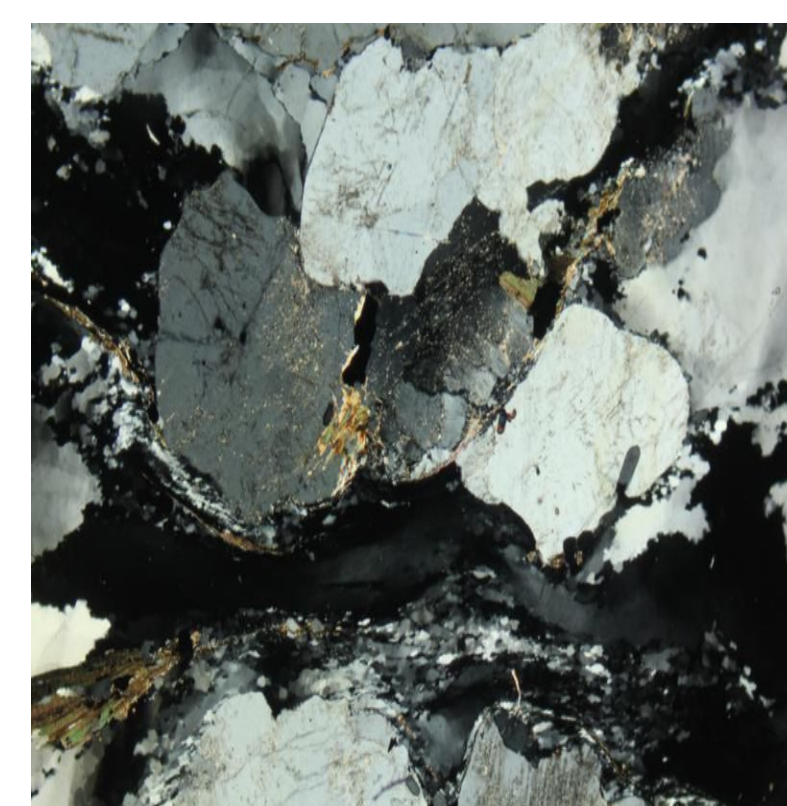
Dataset



Sigma-Clast



Sigma-Clast

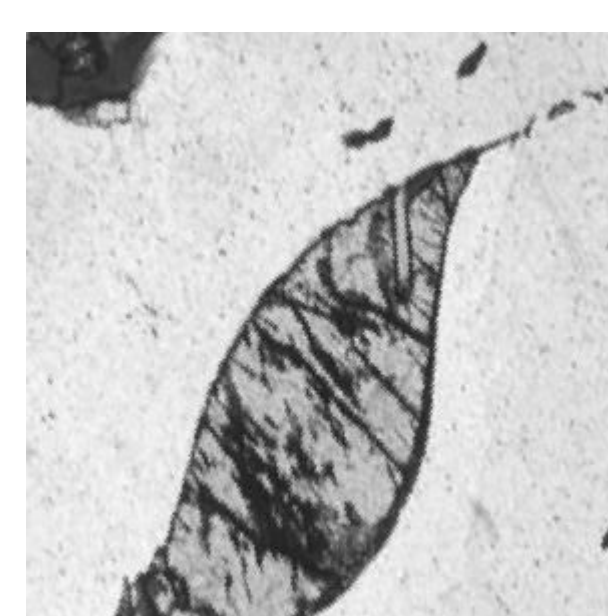


Non-Sigma-Clast

Data Augmentation

- Allows for smaller datasets to become larger, as long as data is not augmented to a different classification(ex. Distorting Sigma-Clast image to become more of a Non-Sigma-Clast)

Effects Utilized:
Rotation range: 40°
Height/width shift: 10%
Shear range: 0.2 rad ccw
Zoom: 30%
Horizontal flipping: true
Fill mode: "reflect"



Counterclockwise
Rotation
Zoom



Height Shift
Width Shift
Zoom

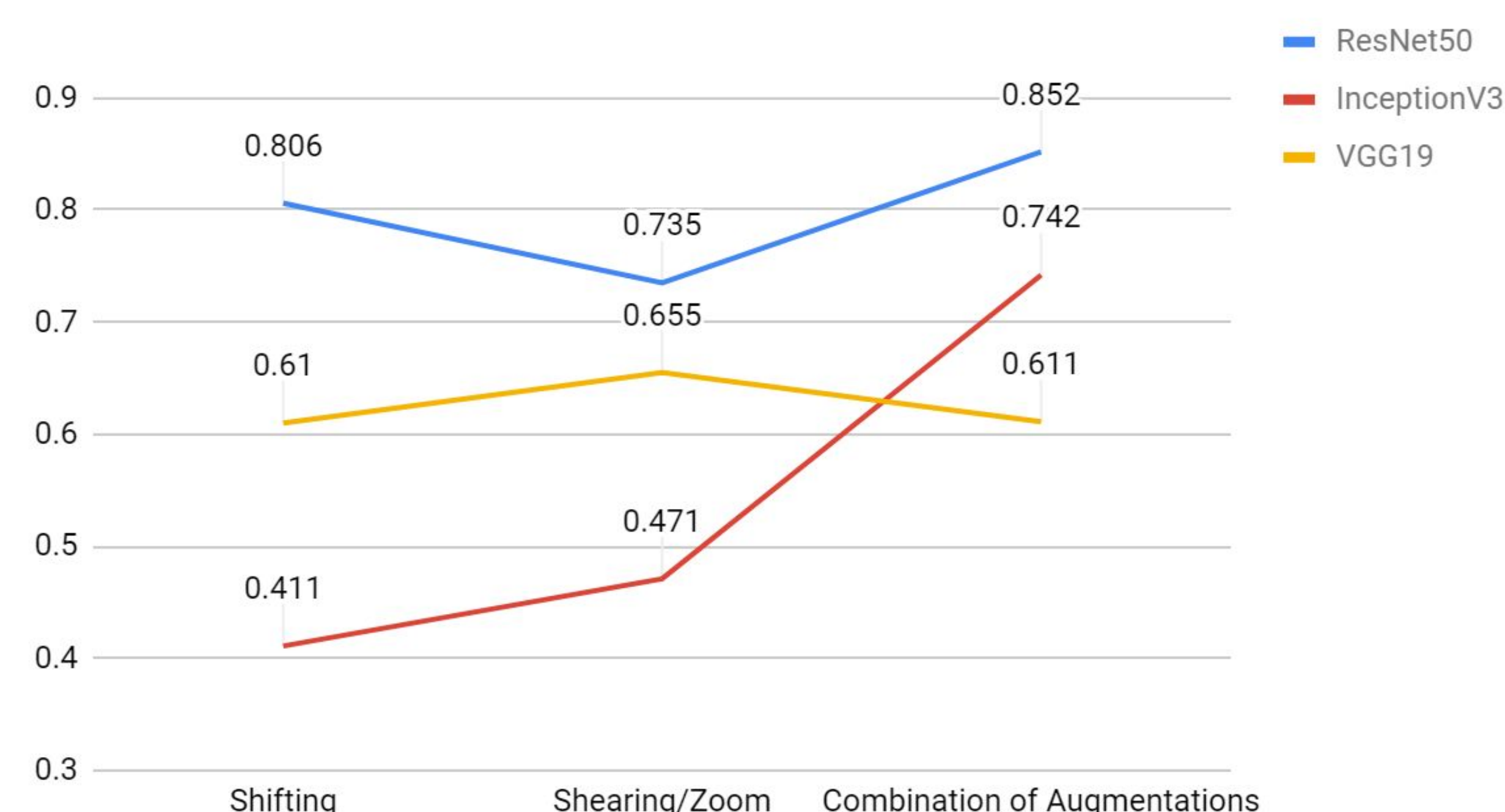


Horizontal Flip
Clockwise Rotation
Filled

Testing Data Augmentations

($n_{non-sigma} = 879$; $n_{sigma} = 100$)

F1 Scores of Augmentation Methods on Different Models

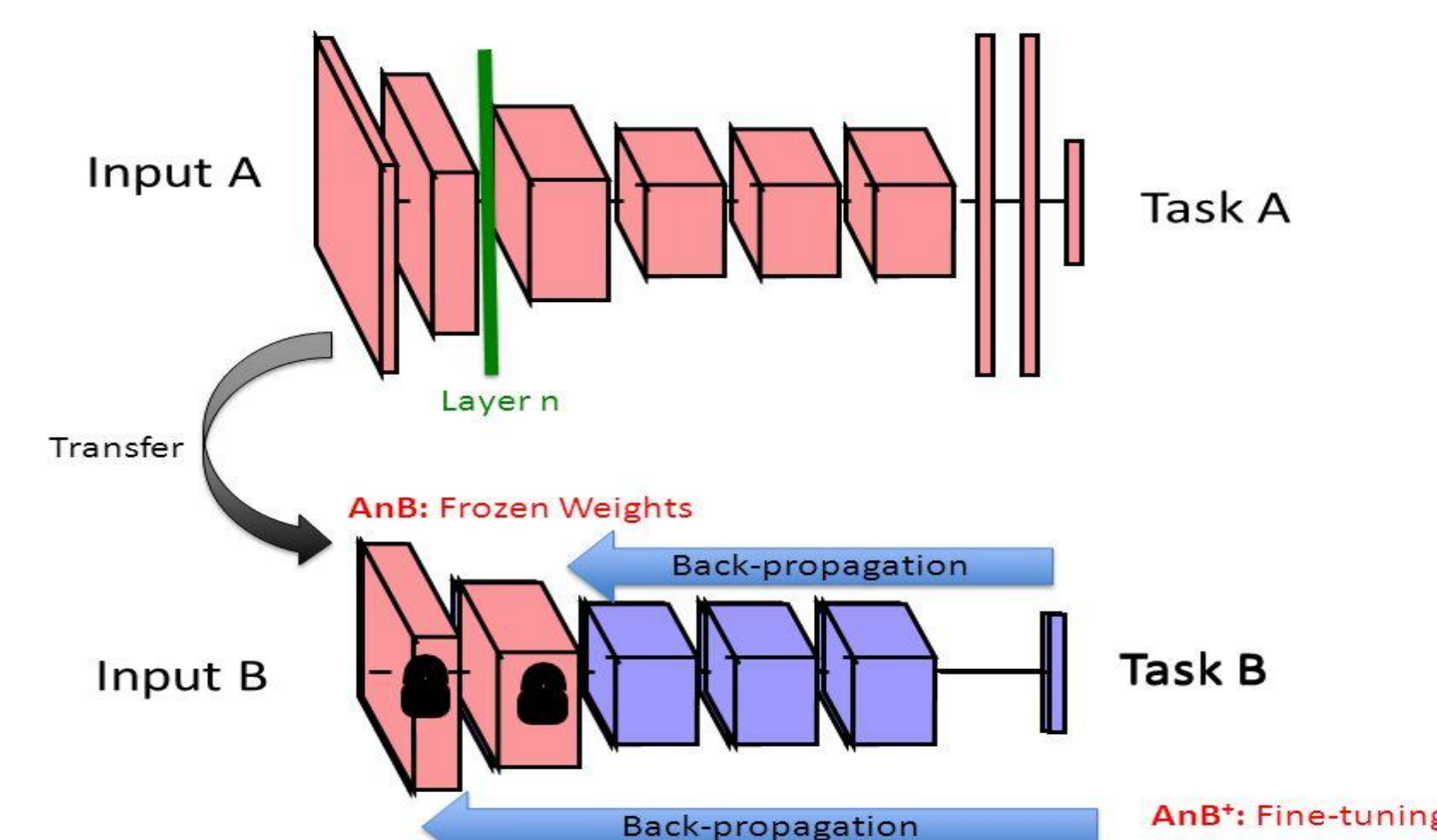


*Combination of Augmentations refers to the augmentations listed under *Effects Utilized* in the above frame

*F1 score is an evaluation metric that is a trade-off between the recall (true positive rate) and precision (fraction of relevant classifications)

Transfer Learning and Fine Tuning

- Allow a Convolutional Neural Network to correctly learn over a very large dataset
- Take the Convolutional Neural Networks and utilize its features instead of creating our own.
- Fine tuning modifies last few layers to ensure we look for the complex structures we want.

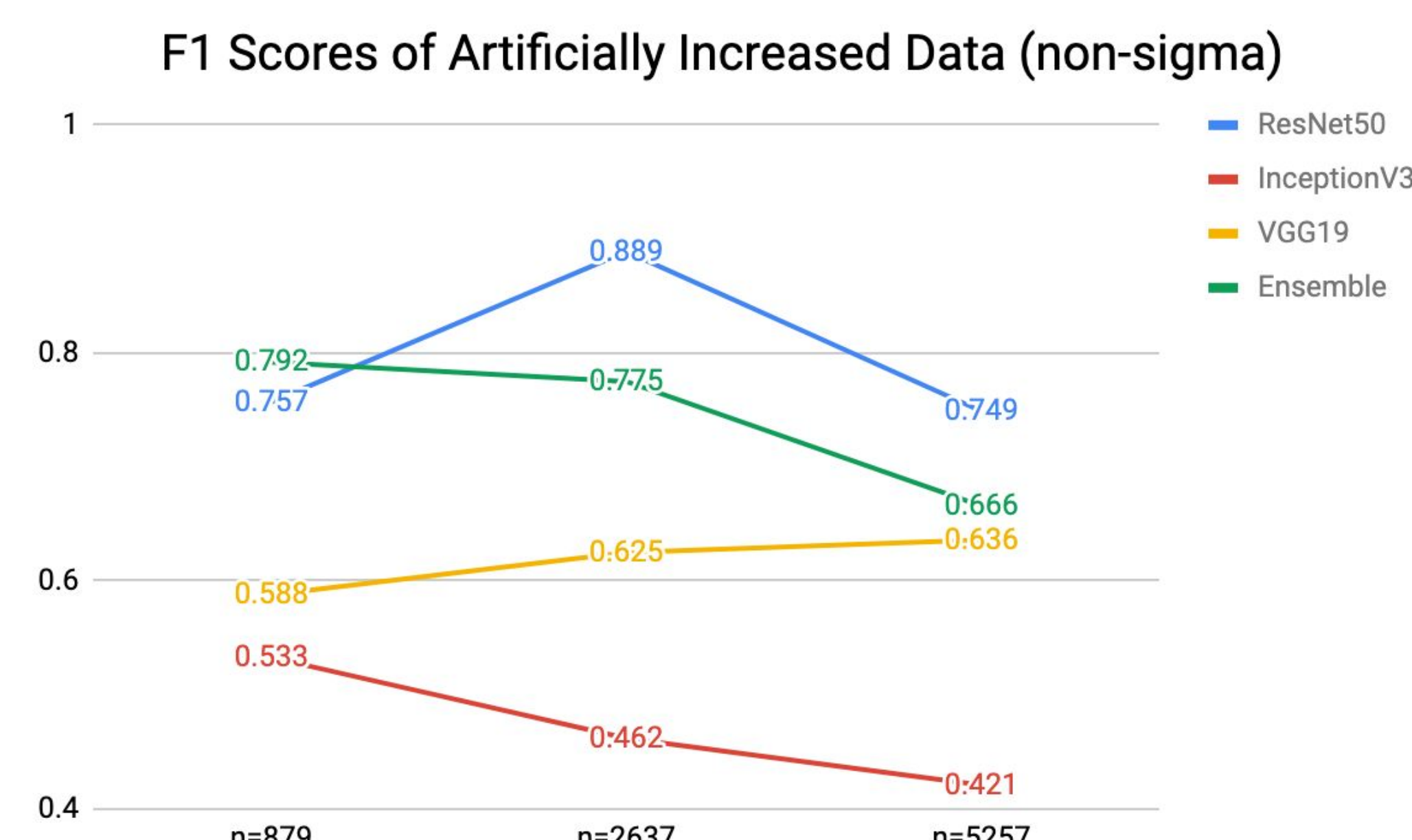


Neural Network Ensembles

- Takes Multiple Convolutional Neural Networks and combines their output.
- This method ensures that we reduce the variance between multiple models by taking the average of each model to compute the classifications

Artificially Increasing the Dataset with Oversampling ($n_{non-sigma} = 879, 2637, 5257$; $n_{sigma} = 100$)

- We can artificially increase the largest class of data we have, then use oversampling to create copies of the smaller dataset to match



Best Combination

- Used Methods: Oversampling with $n \sim 3000$ and Fine Tuning, on ResNet50
- F1 Score: 0.919

Confusion Matrix	Non-Sigma	Sigma
Non-Sigma	791	0
Sigma	5	25

Full Stack Architecture for Web-based Classification

Front-End: React JS

Handles the user interface, sets necessary objects to be sent to the backend.

HTTP Client: Axios

"Connects" the front-end to the back-end using HTTP.

Microframework: Flask

Designed for Python; handles the HTTP requests that come from Axios.

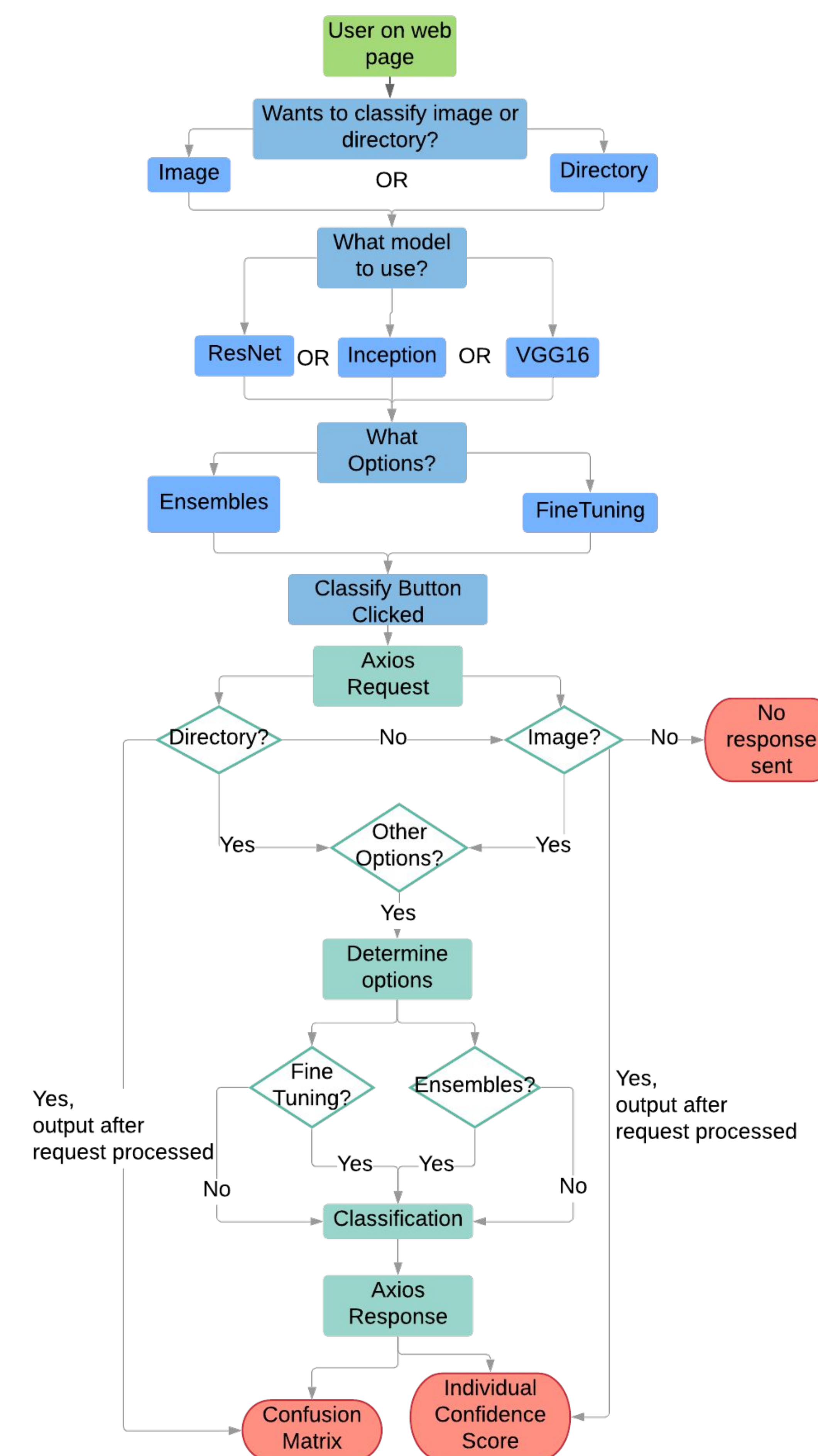
Back-End: Python

Creates functionality to resize and classify images

Classification: Keras and Tensorflow

The libraries that allow for the prediction and classification of images.

Process Flow for Web-based Classification



Conclusion and Future Research

- Significant improvement of accuracy can be seen among the system of networks.
- Being able to classify the rotation of a Sigma-Clast (i.e. Counter-Clockwise/Clockwise)
- Allow for K-Fold cross validation evaluation
- Generalize the model for multiclass classification.
- Web Application
 - Enhance UI -- color scheme, fill whitespace effectively
 - Allow for prediction options such as ensembles and fine-tuning
 - Host application on a live site

Acknowledgements

Special thanks to Earthcube NSF Grant for funding this research, as well as Dr. Gurman Gill for guiding the team