Damage Detection: A machine learning classification of hurricane flood damage

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MUSA 650: Geospatial Machine Learning in Remote Sensing

Hurricane Flood Damage

Natural disasters, including hurricanes, have become more pervasive due to climate change. The US now experiences three times as many damaging hurricanes than we did 100 years ago.

Such events cause intense damage to critical infrastructure. This damage and destruction can result in the loss of homes, businesses, emergency and transit systems, and lives.

New York Times

Inside Climate News

Damage Assessment

Damage assessment is a critical step in emergency response efforts.


Huitt-Zollars

Accurate damage assessments are key to informing response and recovery.


PDH Academy

It helps responders understand the the structural loss, displacement, and state of natural resources in the area.


Property Casualty 360

Traditionally, assessments are conducted by ground survey, which relies on resources and time that can be limited after a disaster.


Hakai Magazine

Remote Sensing

Remote sensing can facilitate faster and more resource efficient assessments following a disaster.

Remote sensing tools can:

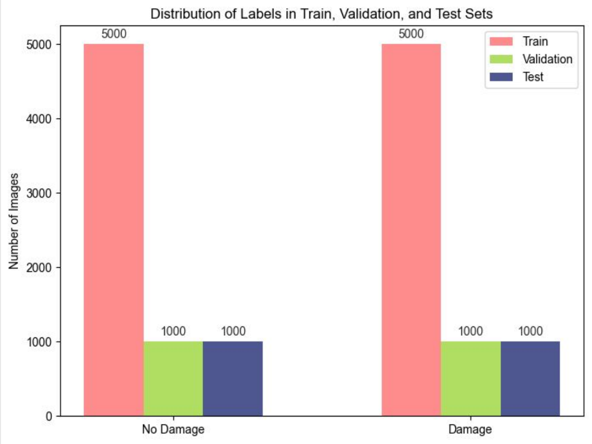
- Detect damage
- Predict future damage
- Analyze total loss

Leveraging the power of machine learning in remote sensing after a flood event, planners can identify infrastructure that has been damaged and see if there is a spatial pattern to infrastructure damage.

Our Project

Goals:

- Build models to classify building damage after hurricane
- Use binary classification systems to identify buildings with damage and without damage

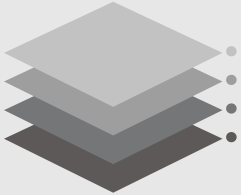


Data:

- Satellite Images of Hurricane Damage (Kaggle)
- Binarized, ground truth labeled images:
    - train_another : the training data; 5000 images of each class
    - validation_another: the validation data; 1000 images of each class
    - test_another: the unbalanced test data; 8000/1000 images of damaged/undamaged classes
    - test: the balanced test data; 1000 images of each class

Our Models

Convolutional Neural Network

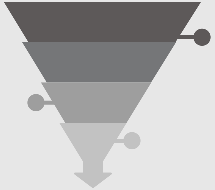


2 Convolutional layers (3x3 filter and stride 1), separated by batch normalization, max pooling (2x2), and dropout layers + flatten and 3 dense layers

Transfer Learning: VGG16

16 weighted convolutional layers (3x3 filter and stride 1) and max pooling layers (2x2 filter and stride 2) + additional flatten and dense layers

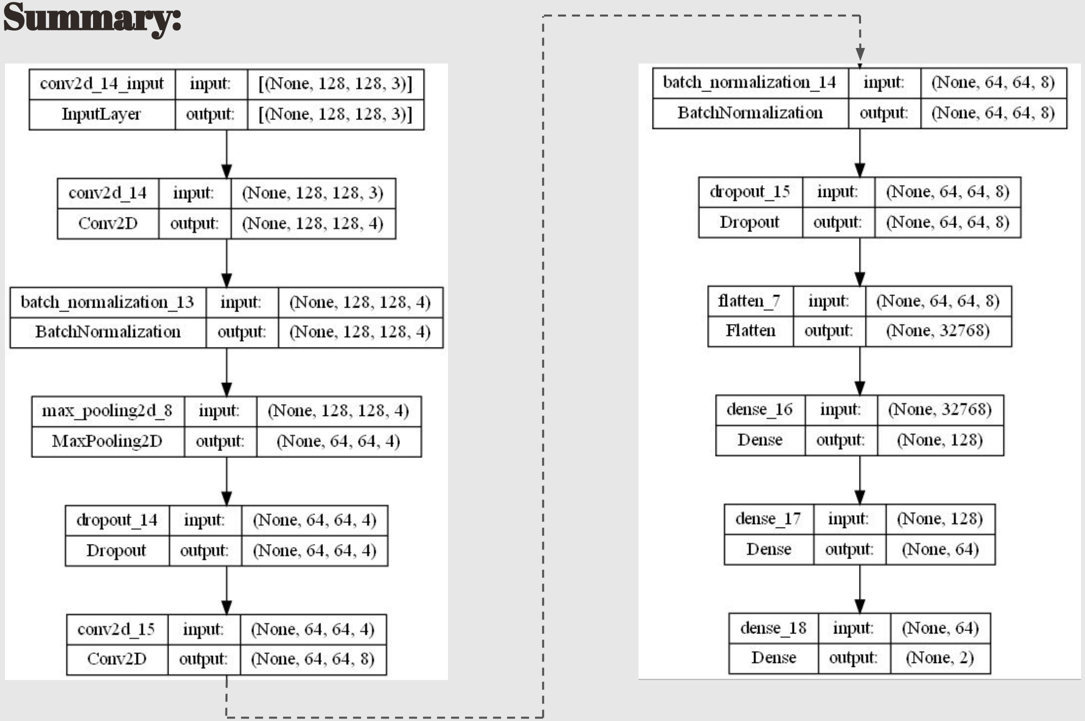
Residual Neural Network



2 sets of 2D convolutional layers, batch normalization, ReLU, another 2D convolution, another batch normalization, with Max Pooling 2D with increasing inputs and a final dense layer

Model 1: CNN

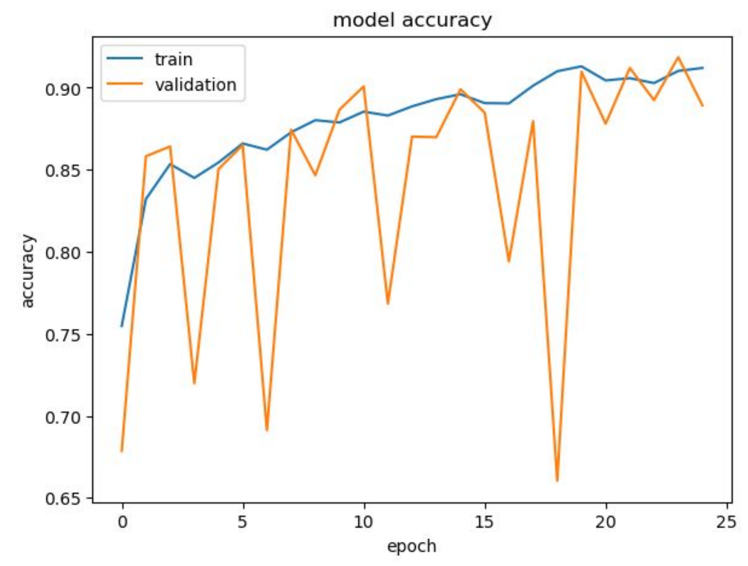
Summary:



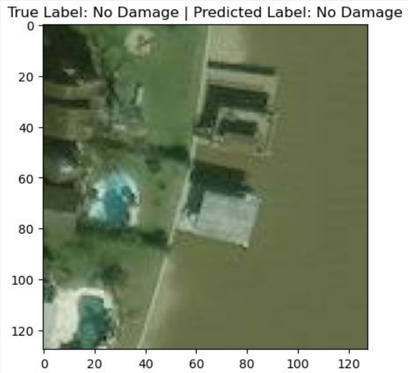
Model 1: CNN

Test loss: 0.267

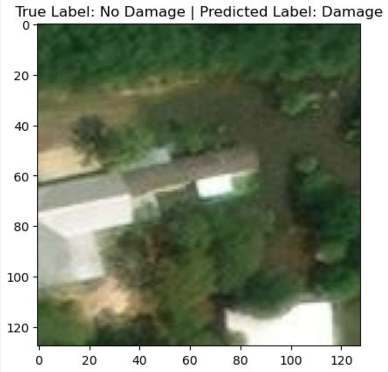
Test accuracy: 0.884

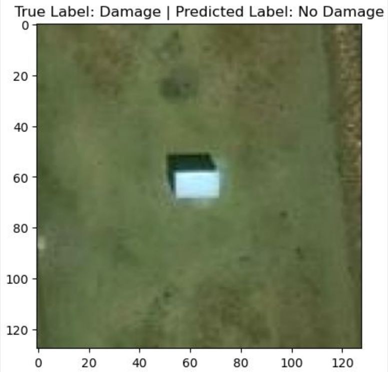


Model 1: CNN



Correctly Classified

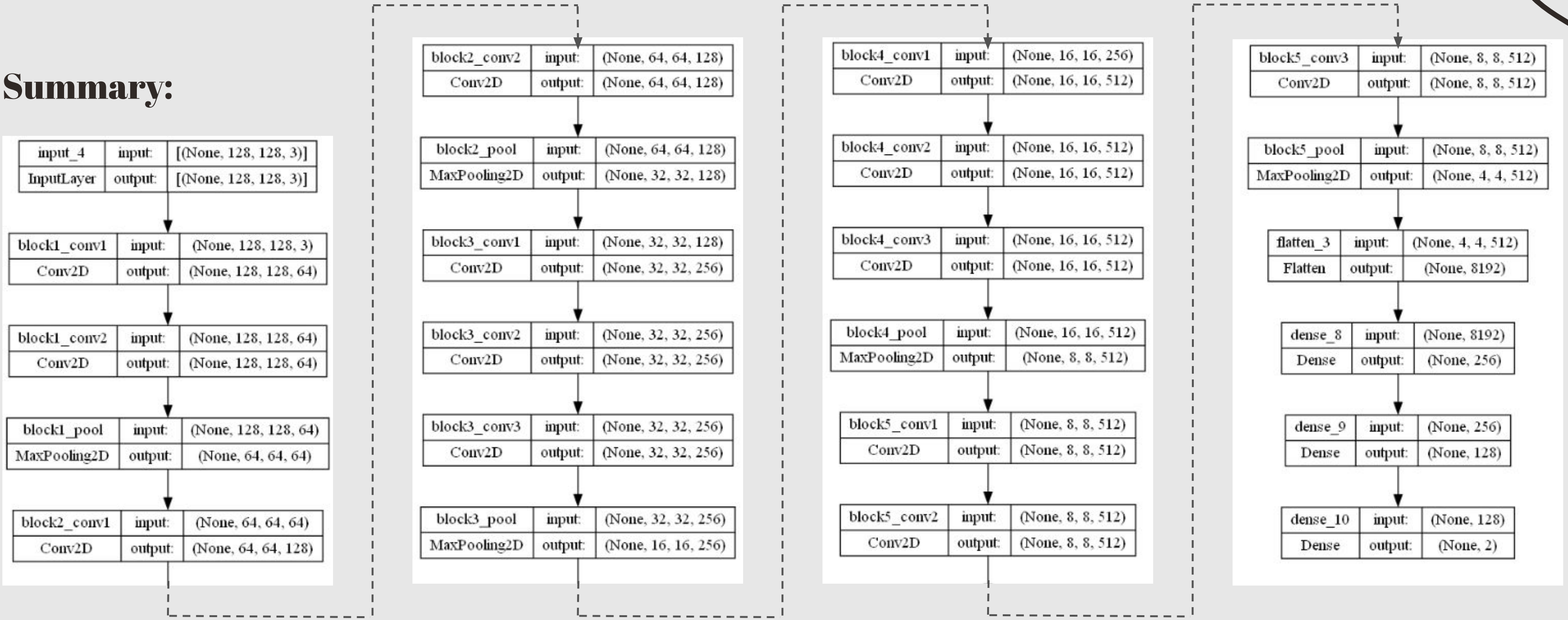




Incorrectly Classified

Model 2: VGG16

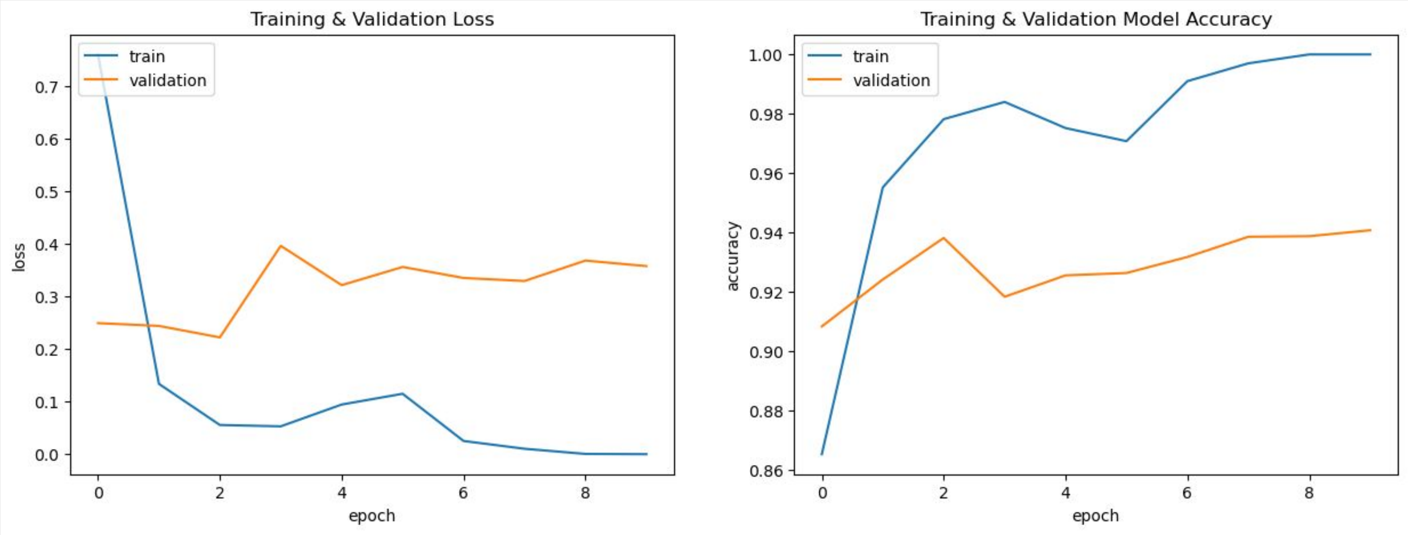
Summary:



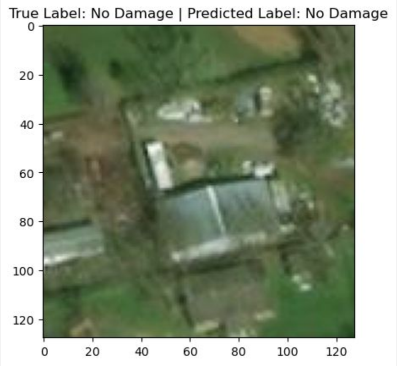
Model 2: VGG16

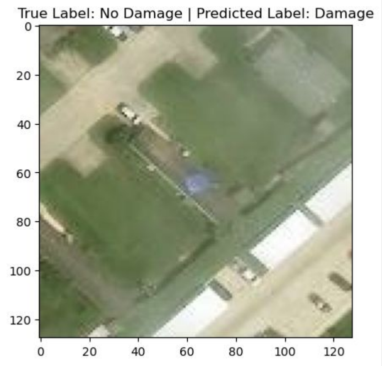
Test loss: 0.3578

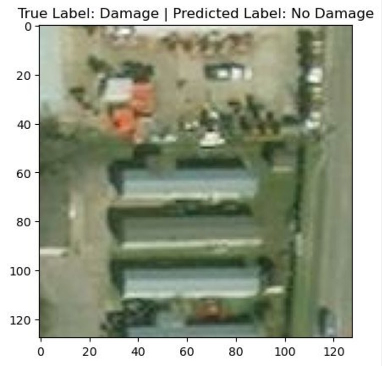
Test accuracy: 0.9408



Model 2: VGG16







Correctly Classified

Incorrectly Classified

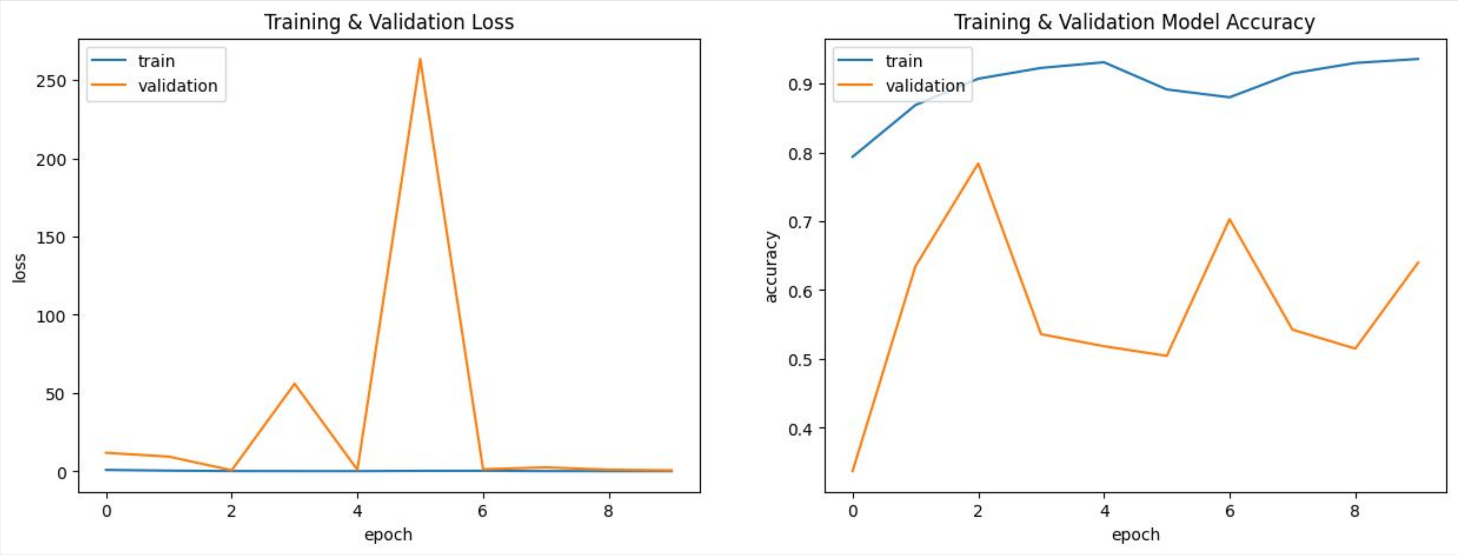
Model 3: ResNet

To see full model architecture, click this link:

https://github.com/jtrummler/MUSA650_Final/blob/main/ResNetmodel.png

Model 3: ResNet

Test loss: 0.673 **Test accuracy: 0.626**



Model Comparison

Convolutional Neural Network

Accuracy: 0.884
Loss: 0.257

Transfer Learning: VGG16

Accuracy: 0.941
Loss: 0.357

Residual Neural Network

Accuracy: 0.626
Loss: 0.673

Discussion of Outcomes

- CNN had the lowest loss and a pretty high accuracy, likely due to the model’s simplicity, low likelihood of overfitting, and the binarized outcome
- VGG-16 had a strong loss and the highest accuracy, likely due to the model’s pre-exposure to unseen data, making it accurate and generalizable
- ResNet had the weakest loss and accuracy scores, likely due to the complexity of the model’s architecture and not using pre-trained ResNet architecture

Conclusion

Remote sensing is a powerful tool that can be leveraged for damage assessment and recovery operations after disasters.

Our models show that classifying post-hurricane satellite images can be successfully classified using machine and deep learning methods.

The models presented here had accuracies ranging from 62% - 94%. Our VGG16 model had the highest accuracy, while the CNN model had the lowest loss. The ResNet model had the lowest accuracy and highest loss.

Jupyter Notebook

CNN

Thank you!