Classifying Disaster-Induced Images Via Computer Vision

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https://youtu.be/UwdOYI2VrcI

DATA 200S

Introduction

Fast and accurate evaluation is necessary for disaster response

Limitations of traditional disaster classification methods:

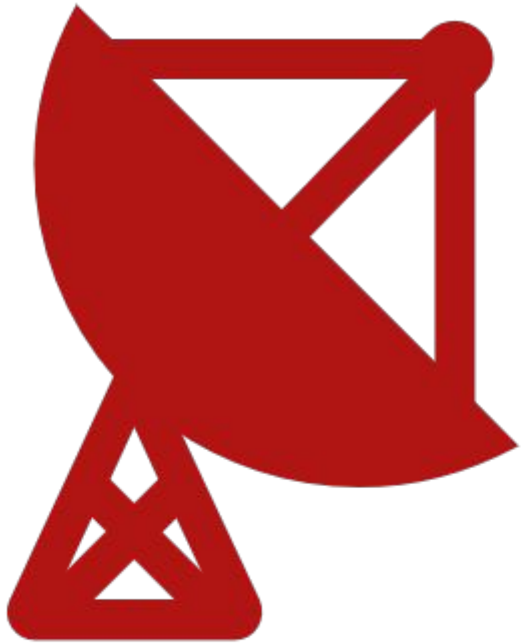
- Time and cost
- Inaccuracy

Project Objective and Dataset

Novel application of computer vision for disaster classification of satellite imagery

As proof of concept and confidence in model for two classification tasks:

- **Task A:** Flood vs Fire Image Classification
- **Task B:** Evaluating Hurricane Disaster Levels



Data Extraction and Origin

- Use data from the **xBD Dataset** from the Maxar/DigitalGlobe Open Data Program
- Contains **satellite imagery of buildings** across varying disaster types (fire, flood, and hurricane) and damage levels (0-3)

EDA and Data Augmentation

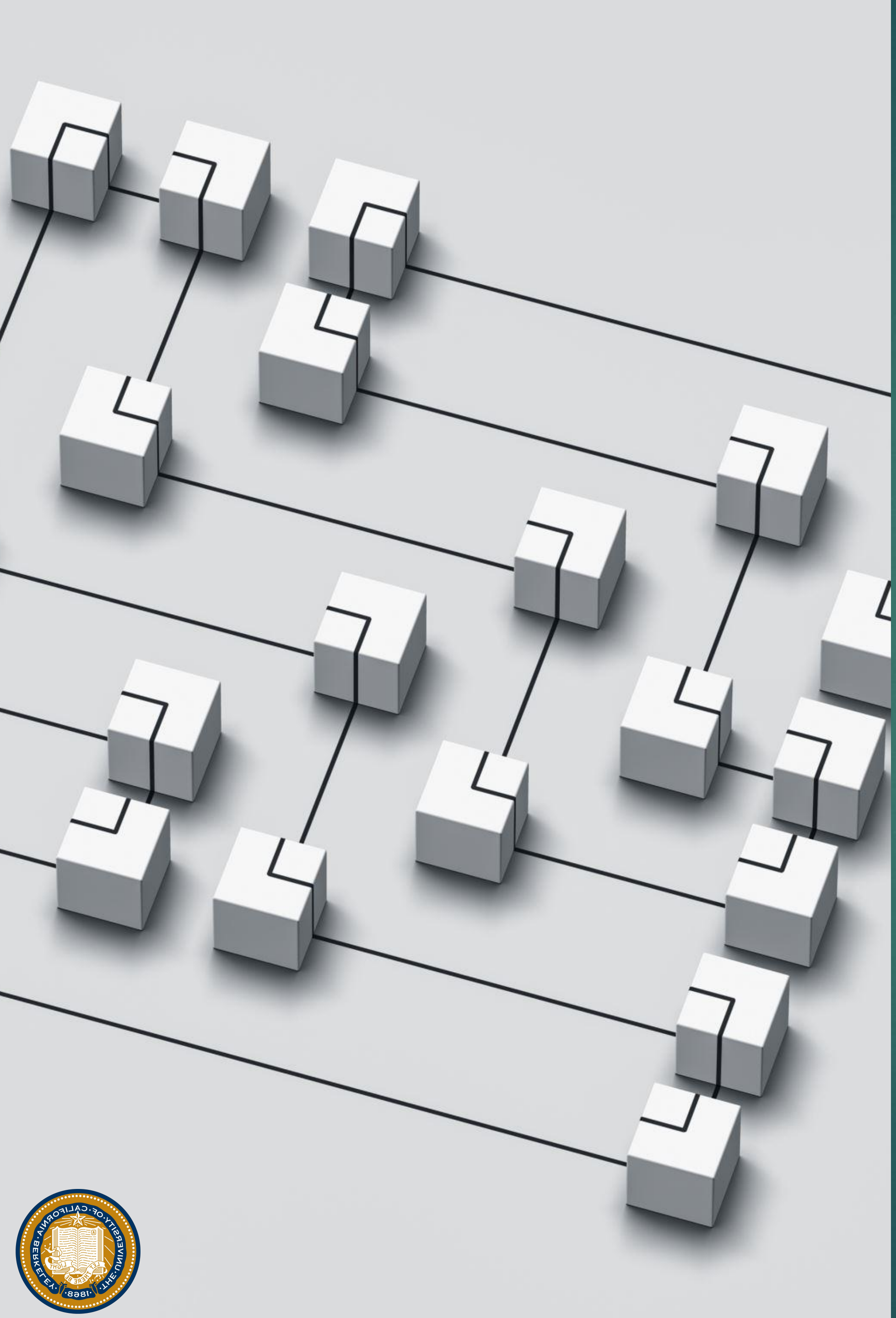
Key Issues:

- Label imbalance
- Image size imbalance

Techniques used:

- Under/over sampling
- Class weighting
- Image rotation and resizing
- Pixel intensity normalization

Damage Level **Disaster Type**	**0**	**1**	**2**	**3**
Fire	7204	69	43	1064
Flood	6734	114	97	59
Hurricane	2631	5236	1544	1740



Model Overview (Architecture)

Task A

- PCA Compression + Logistic Regression
- Convolutional Neural Network

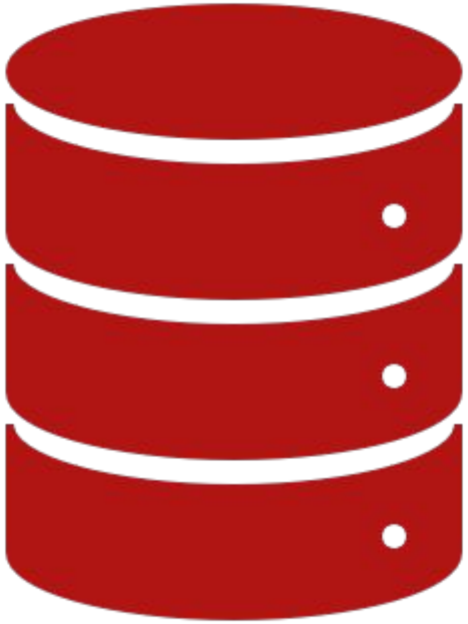
Task B

- Convolutional Neural Network
- Hyperparameter settings
  - Batch size
  - Width and depth

Model Architecture 1 - Logistic Regression

Architecture:

- Flattened data for model input
- Logistic Regression
- Data compression with PCA



Model Architecture 2- Convolutional Neural Network

VGG16 Pretrained model

- Lower Compute, Less Memory, and quicker to train and predict!!!

Flattened data for Inference

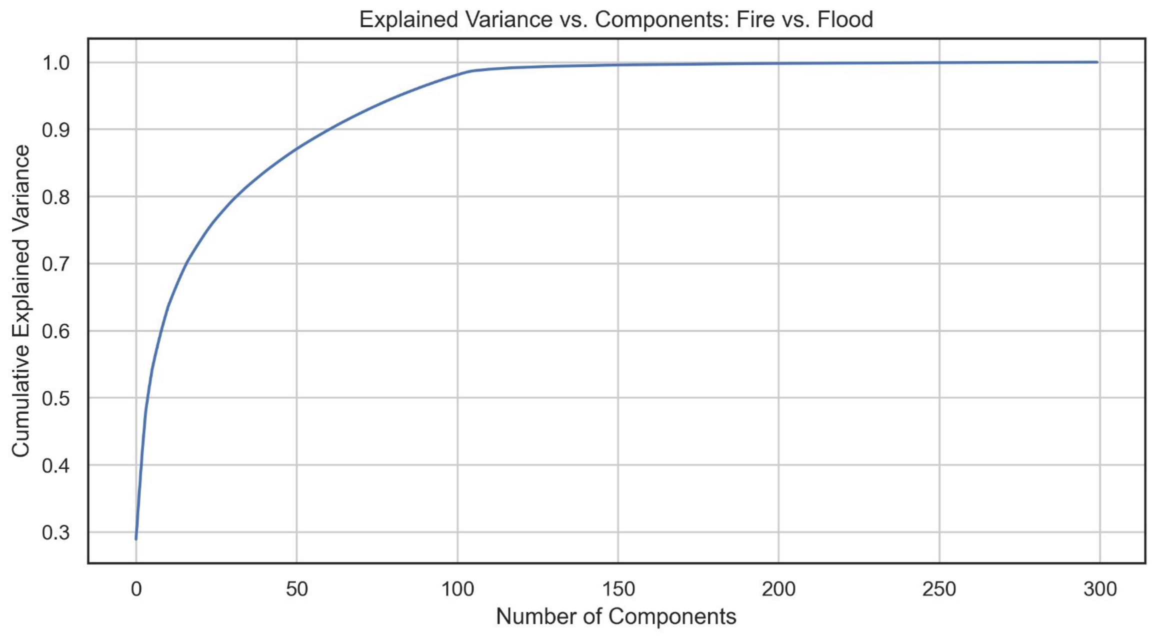
Hyperparameter tuning for optimal performance

- Batch size
- Learning rate
- Network width and depth

Fire/Flood Classification: Logistic Regression

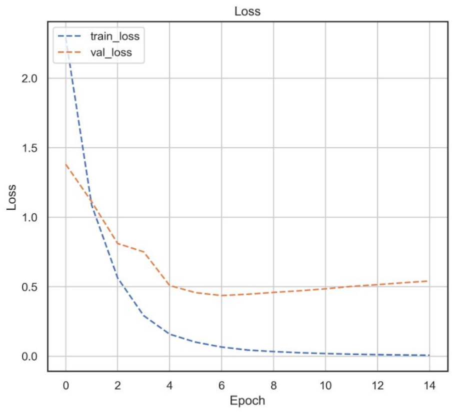
Logistic regression model shows adequate accuracy on fire-flood classification task.

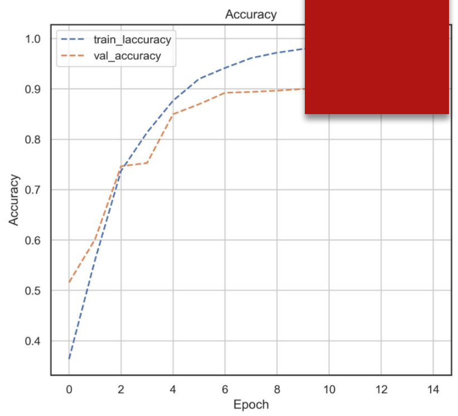
Explained variance depends on the number of features (i.g. 10x10 image show here)



Fire/Flood Classification: CNN

- CNN outperforms logistic regression model performance on fire-flood classification task with little overfitting.

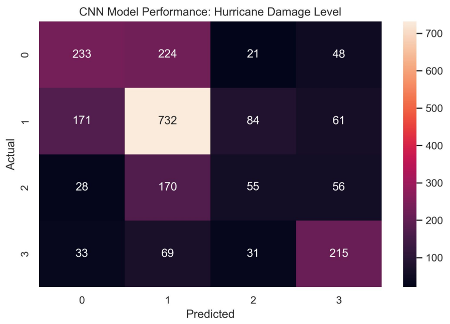




Damage Level	Precision	Recall	F1-Score	Support
Flood (0)	0.9567	0.9622	0.9594	1401
Fire (1)	0.9682	0.9636	0.9659	1676
Accuracy			**0.9630**	3307
Macro Avg	0.9625	0.9629	0.9627	3307
Weighted Avg	0.9630	0.9630	0.9630	3307

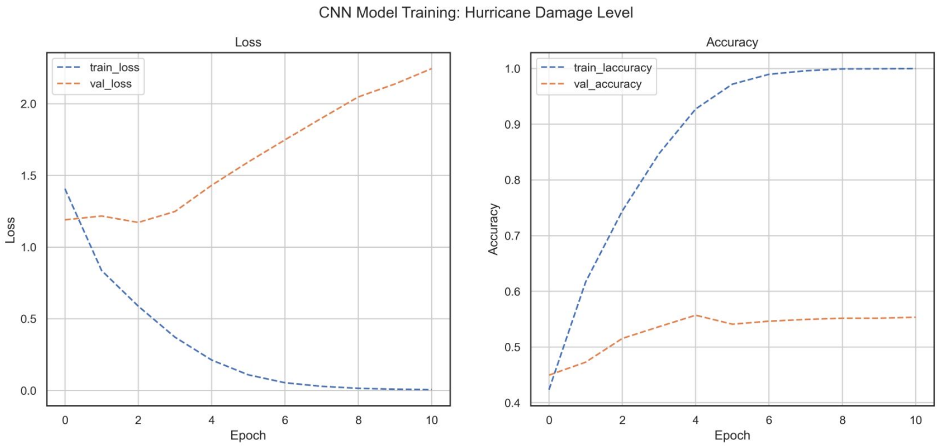
Hurricane Damage Classification: CNN

- CNN training suggests high overfitting and imbalance of training and validation datasets.



Damage Level	Precision	Recall	F1-Score	Support
0	0.50	0.44	0.47	526
1	0.61	0.70	0.65	1048
2	0.29	0.18	0.22	309
3	0.57	0.62	0.59	348
Accuracy			**0.55**	2231
Macro Avg	0.49	0.48	0.48	2231
Weighted Avg	0.53	0.55	0.54	2231

Table 4: CNN accuracy on validation data for task B classification.



Conclusions, Limitations and Future Work

Insights on model complexity vs. performance

Benefits of using a pretrained VGG16 model

Potential for model improvement with augmented datasets

Limited compute and memory limited model complexity

Future directions:

Correlate before and after images

Combine satellite images with ground photos for comprehensive analysis

Meet our team

REFERENCES

5.1 References

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