GIN & TONIC : Graph Infused Networks with Topological Neurons for Inference and Classification

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Introduction

Once a natural disaster strikes, volunteers must manually identify and classify the damage of the affected buildings. Inspired by the XView2 challenge, our project aims to automate the post-disaster building damage classification - to empower a speedy rescue ops around the globe.

Our hypothesis is we can redefine the natural disaster damage classification problem as a graph-theory and machine vision problem. To achieve this, we designed a hybrid deep learning model, combining a GCN + a CNN and other experiements to vastly improve damage classification over XView2's baseline model.

Data

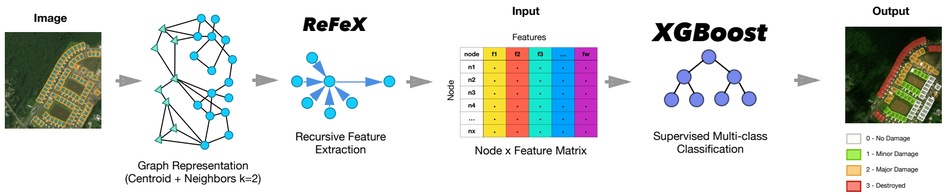
Figure 1: Satellite images from xBD dataset. Pre & post-disaster

The xView2 challenge provided the xBD dataset, which is the largest and highest quality public data set of expertly annotated high-resolution satellite imagery available online.

The data consists of: 1) an image data set 850,736 buildings within 22,000 images spanning 45,361 square kilometers for 19 disaster events, 2) a labeled data set of metadata e.g. image uid, building coordinates, building labels, damage classification (0- No Damage, 1- Minor Damage, 2- Major Damage, 3- Destroyed), and wkt polygon shape.

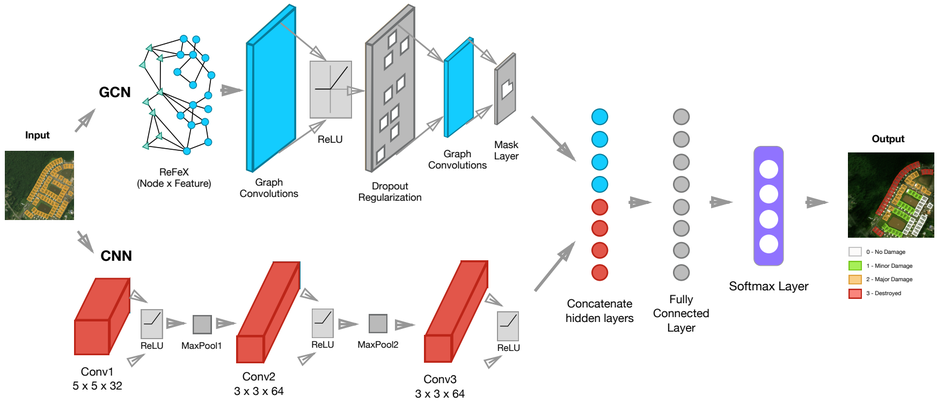
Method

1. A Classical ML Approach: ReFeX-XGBoost



The ReFeX-XGBoost method combines feature extraction using Graph theory and decision tree based classification. First, we build a graph based on spatial characteristics of buildings. ReFeX then extracts 38 spatial features for nodes. Finally, node feature and label data is fed into a XGBoost to train the multi-class classifier.

2. Proposed Deep Learning Approach: Hybrid GCN + CNN



The proposed model f(·,·) is defined as a combination of a Graph Convolution Network and a Convolutional Neural Network. The proposed model is formerly defined as

$$f(v_i, x_i) = F(W_k \cdot \sigma([W_{k-1} \cdot AGG(h_u^{k-1}, \forall u \in N(v_i)), C^{k-1}(x_i)]))) \quad (1)$$

where u represents the nearest neighbors of v_i and $AGG(h_u^{k-1}, \forall u \in N(v_i))$ is the GCN component of the model while C^{k-1} represents the CNN component.

This model was trained using: 124,284,320 total params, 121,795,616 trainable params, 2,488,704 non-trainable params. The lower half of the Resnet-50 model weights was frozen to take advantage of the low level feature maps that were obtained training on imagenet data. The upper portion was trained to provide feature maps specific to damaged buildings.

Results & Discussion

Table 1: Model Performance for Damage Classification

Damage Type	Model	Precision	Recall	F1
No Damage	CNN Baseline	0.857	0.451	0.591
	ReFeX + XGBoost	0.664	0.866	0.752
	GCN + CNN	**0.931**	**0.943**	**0.937**
Minor Damage	CNN Baseline	0.073	**0.484**	0.127
	ReFeX + XGBoost	**0.485**	0.290	0.363
	GCN + CNN	0.447	0.411	**0.428**
Major Damage	CNN Baseline	0.242	0.093	0.134
	ReFeX + XGBoost	**0.642**	0.388	0.484
	GCN + CNN	0.549	**0.466**	**0.504**
Destroyed	CNN Baseline	0.420	0.623	0.502
	ReFeX + XGBoost	0.612	0.446	0.516
	GCN + CNN	**0.744**	**0.777**	**0.760**

The proposed model performed significantly compared to the other models. As demonstrated, it leveraged CNN and graph structure to improve F1 scores across the different categories of damage classification.

Conclusion/Future Work

Utilizing graph theory in conjunction with a powerful convolutional neural network (CNN), a model was proposed that out-performed baseline values previously reported using a baseline Resnet-50 architecture as well as a powerful classical machine learning algorithm called XGBoost. The proposed model improved upon recall, precision and F1 scores in each of the different damage categories by statistically significant margins.

Future research will focus on methods of defining edges between building images that may be useful in better assessing building damage for minor and major damage categories. Improving building damage assessment in AI can empower rescue efforts around the globe when natural disasters strike.