Taming Big Remote Sensing Data to Aid First Responders in Damage Assessment in a Post-Flood Scenario

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Introduction

- Creating tools and technologies to process and analyze large quantities of raw images is vital as remote sensing data continues to grow so large that much of the data remains untapped.
- In a post disaster scenario, ariel images of an affected region can provide information that first responders are able to utilize to plan rescue missions.
- The objective of this research project is to explore the performance of Artificial Intelligence techniques in **rapid** disaster **damage assessment** using satellite imagery.
- The outcome is a system that can help first responders quickly explore their data, finding images that are important to the mission, while ignoring those that are not.

AI4HDR-IR System

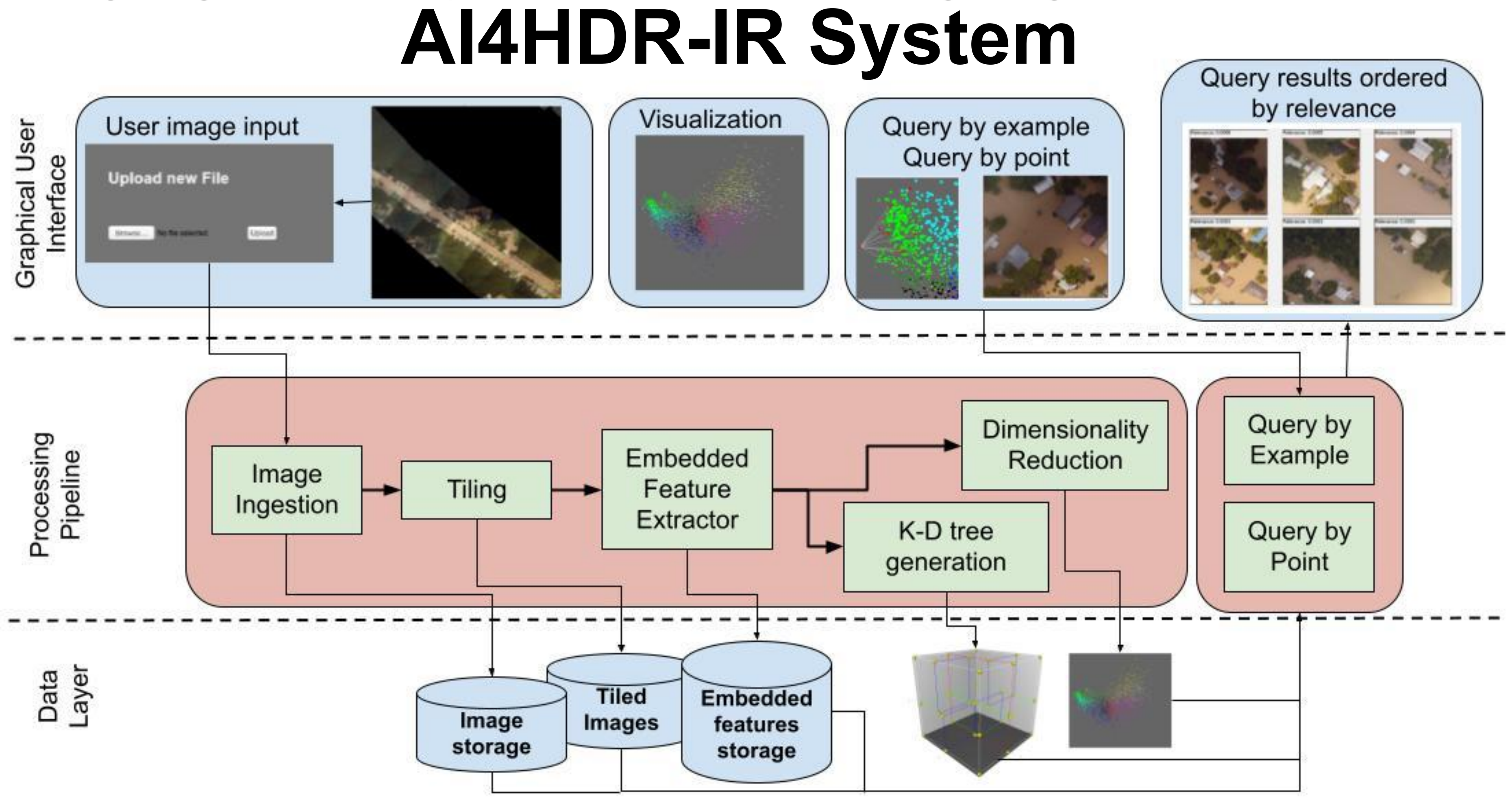


Figure 1: Components of the entire image processing and retrieval pipeline.

- The top layer represents the features available through the user interface: image upload, embedded feature visualization, interactive 3D point cloud, example and point cloud query.
- The middle layer shows the Artificial Intelligence for Humanitarian Disaster Response Image Retrieval System (AI4HDR-IR) system modules: image tiling, embedded feature generation, feature vector dimensionality reduction, and K-Dimensional Tree (KDTree) generation.
- The bottom layer shows the storage requirements: unprocessed user-uploaded image, image tiles and their corresponding feature vectors, and finally the KDTree and projected feature vectors are cached for quick access.

Implementation Details

- The major challenge of this project was dealing with the time constraint present in a post-disaster scenario. Image analysis must happen quickly if the results are to be useful to first responders.
- For the above reason, robust training sets are unavailable to train supervised learning algorithms, so a transfer learning approach was adopted.
- A pre-trained convolutional neural network, VGG16, was found to be useful in extracting pertinent features from images.
- The features are generated from the output of the second to last layer. A new model was created by removing the final classification layer of the VGG16 network.
- To quantify image similarity, we calculate the Euclidean distance between their embedded feature vectors.
- A KDTree was used to search for nearest neighbors in the feature space, providing a search time complexity of O(log N) where N is the number of images in the database.
- The AI4HDR-IR pipeline has been deployed on the Computational Urban Sciences Group's server at ORNL, which consists of four 24-core Intel(R) Xeon(R) Platinum 8268 CPUs and four 32 GB HBM2 NVIDIA Tesla V100S GPUs.

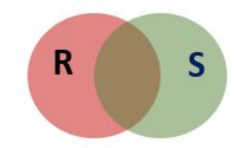
Results

- Four categories of image content were decided on: buildings (with/without standing water), and vegetation (with/without standing water). Twenty samples of each category were selected from a database of 18,000 post-flood images.
- The samples were used to query the system for the top ten most relevant images in the database.
- The precision was calculated for each image sample and then aggregated with the other samples in the category using the harmonic mean. The harmonic mean of the four categories was used as the total system precision (refer Table 1).

Results Cont.

Table 1: Precision of example based query system.

Image Description	Precision Harmonic Mean	
	P@5	P@10
Buildings (No Standing Water)	0.99	0.91
Buildings (Standing Water)	0.55	0.57
Vegetation (No Standing Water)	0.92	0.85
Vegetation (Standing Water)	0.63	0.50
Total System Precision	**0.73**	**0.66**



$$precision = \frac{|S \cap R|}{|R|}$$

R: Set of retrieved images
S: Set of all relevant image in database

Figure 2: A query example of each category showing the top three results: Buildings with no standing water present, buildings with standing water present, vegetation with no standing water present, and vegetation with standing water present (from left to right).

Summary and Future Directions

- We developed an image retrieval system that can be used to find images of interest in a database of remote sensing image archive.
- The results show the overall precision (P@10) of 66% when used to query a database for images relevant to a post-flood assessment.
- In the future we plan to use a convolutional autoencoder (refer Figure 3) trained with remote sensing images as the feature extractor, and explore other distance metrics as well as hash-based image retrieval in order to increase the precision of complex image queries.
- We also plan to use active learning to create classification models which users can train to further hone the query process.

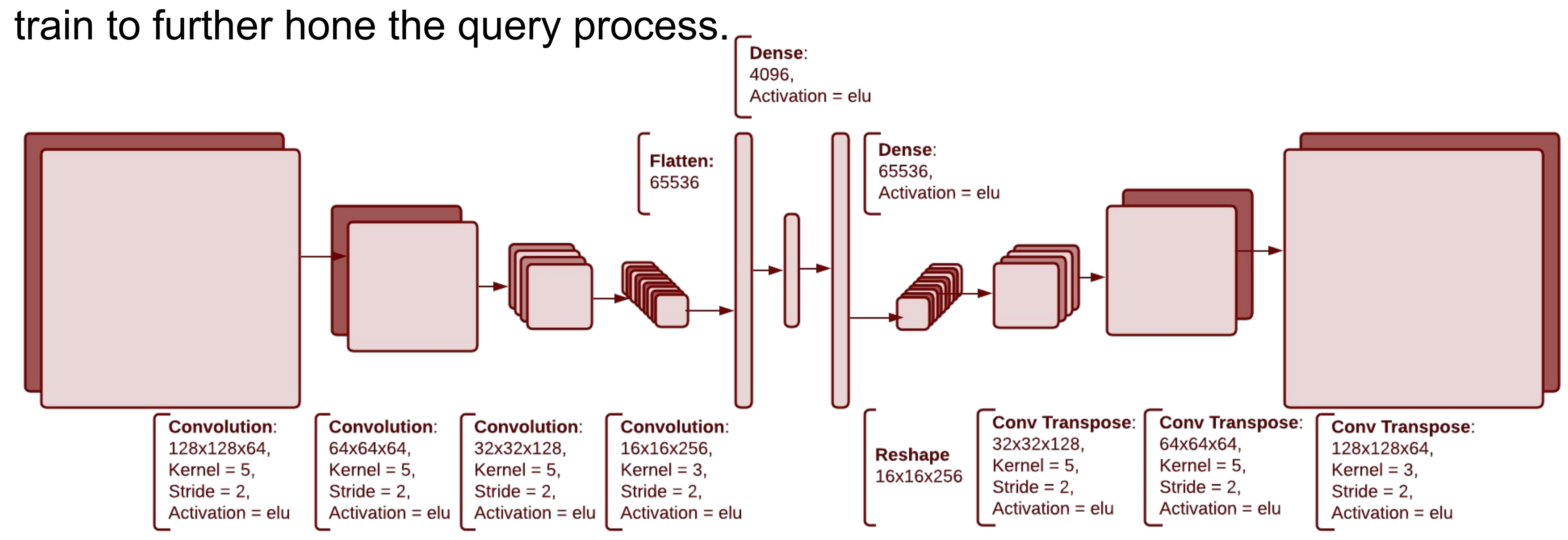


Figure 3: The autoencoder design intended to be used to create a tailored feature extractor.

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