Unearthing Hidden Treasures:
Detecting Critical Minerals from Historical Maps

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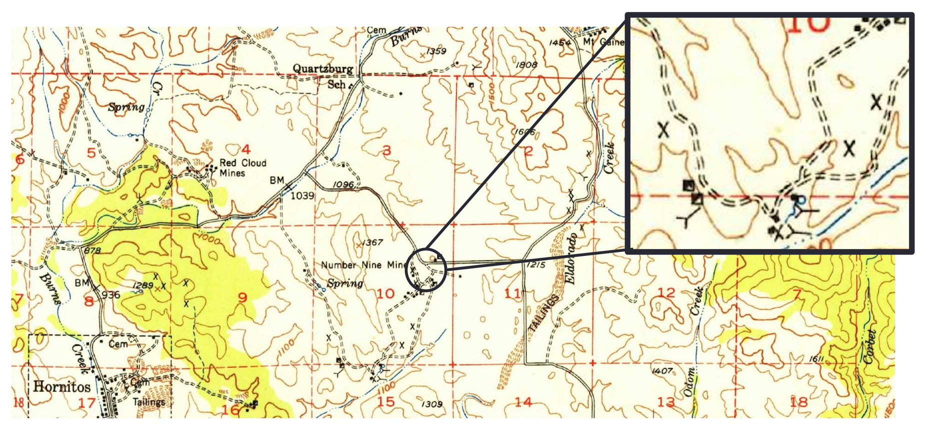
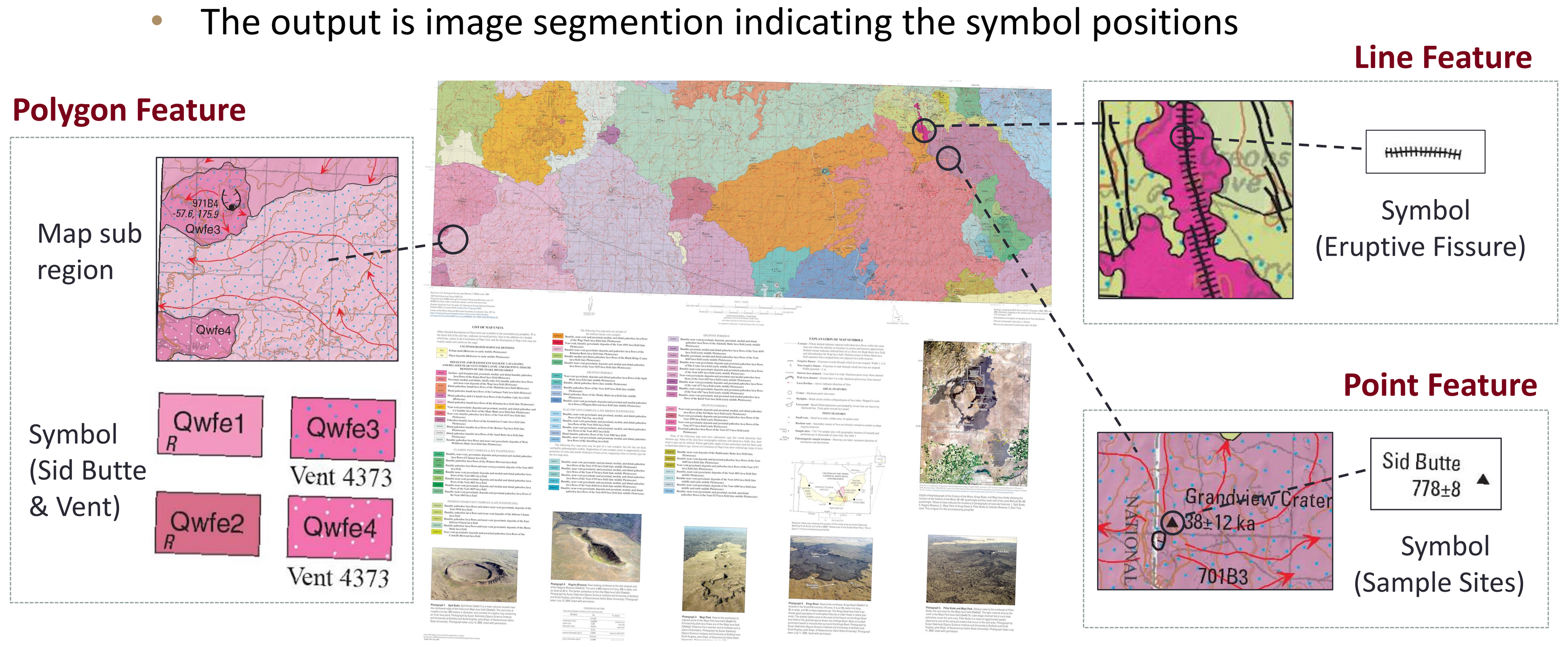
CRITICAL MINERAL DETECTION TASK

- The United States Geological Survey (USGS) collects large volumes of historical maps to **assess the availability of critical minerals**
  - Detect the mineral deposit on the maps (figure below)
  - However, manually reviewing these maps is time-consuming



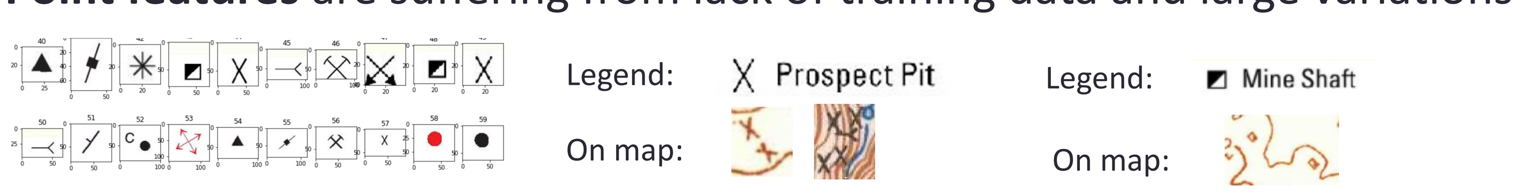
The locations of mineral deposit on a map

- **Task: Given a target symbol, automatically and accurately identify its appearances on the historical maps**
  - Three types of features: lines, polygons, and points
  - The output is image segmentation indicating the symbol positions



CHALLENGES IN FEATURE DETECTION

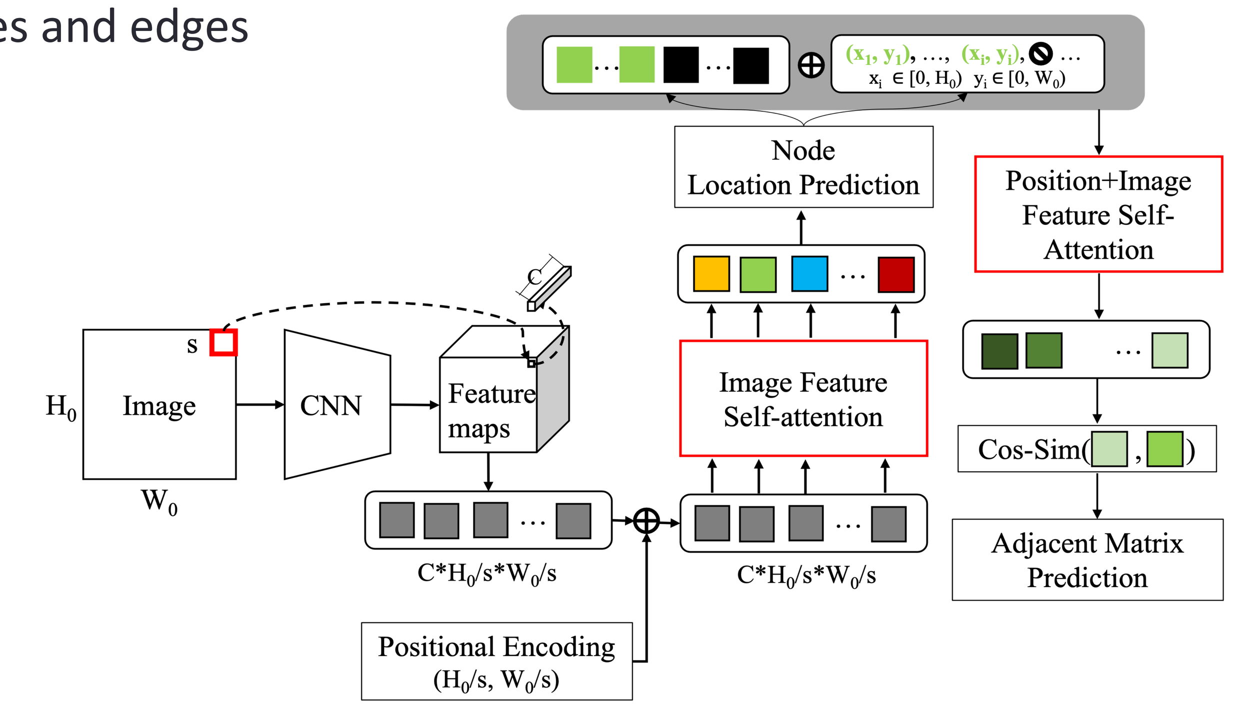
- **Computational** challenge: Need to build individual models for every symbol from the provided map scans
- Some **line features** are similar, easily causing false detection. Also, the detected lines need to be continuous in the segmentation results
- **Polygon features** have various colors, texts, and textures. Simple color-based methods do not handle the symbols within the polygons. Some target symbols are hard to distinguish
- **Point features** are suffering from lack of training data and large variations



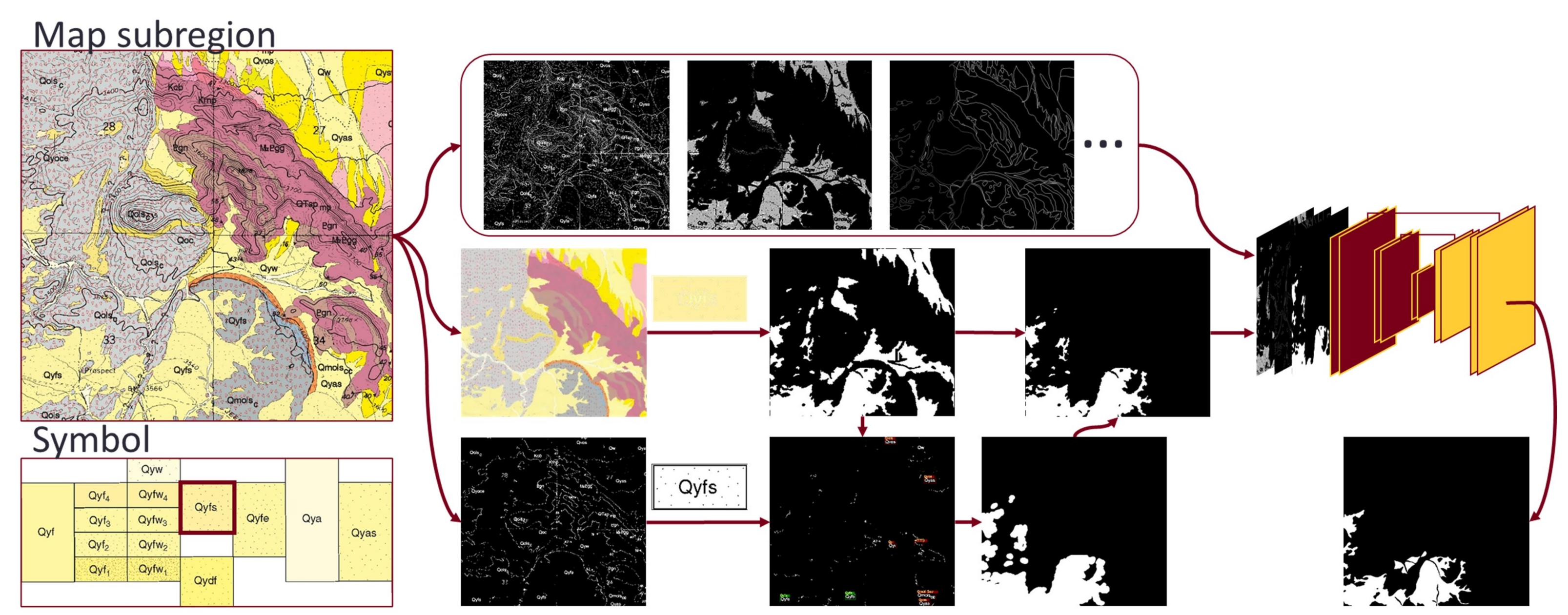
Samples of point feature symbols | Color mismatch | Extreme Size Variation

SYMBOL DETECTION

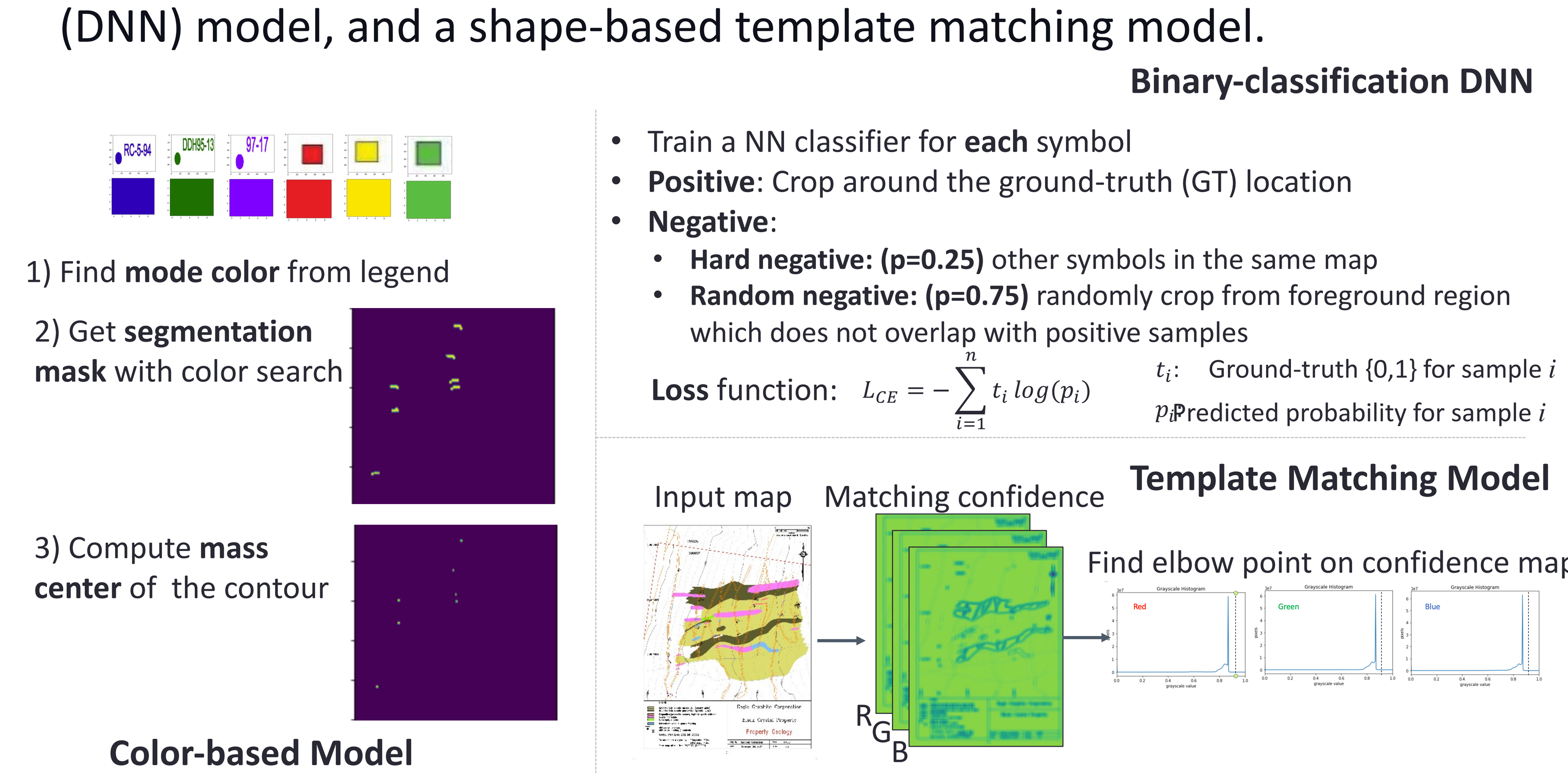
- The **line feature detection** model takes a map image as an input, and leverages attention mechanism to predict the line vectors, consisting of nodes and edges



- The **polygon feature detection** model synergizes the color, pattern of text, and map texture for extracting polygons



- The **point feature detection** module involves three models to handle large variations of symbols: a color-based model, a deep neural network (DNN) model, and a shape-based template matching model.



MSI & RC RESOURCES

The Use of MSI & RC Resources

- Stored large-scale scanned maps (283 in total with a size of ~100G) and intermediate results on the **MSI High Performance Storage**
- Used the **GPU resources** (A100) on MSI for training various deep neural networks.
- We **trained models** for >30 types of line features and 15 types of point features, respectively.

How much did RC resources contribute?

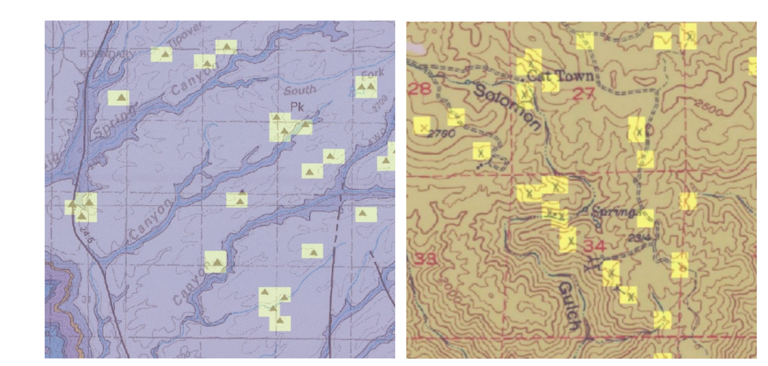
- **MSI high-performance machines** enabled us to preprocess maps in parallel, which greatly speeded up the development of models
- The powerful GPUs allowed us to quickly conduct tests in the **short competition window** (48 hours), which wouldn't be possible with CPU-only machines

EVAL METRICS & RESULTS

Polygon Detection	Median Precision	Median Recall	Median Macro F-1
Color	0.680	**0.971**	0.737
Color + Text	0.747	0.967	0.780
Color + Text + Texture	**0.866**	0.937	**0.823**

Line Detection Visualization (green lines)

Point Detection Visualization



CONCLUSION & ACKNOWLEDGEMENT

- **Our team (ISI-UMN) won the First Place in DARPA Map Feature Extraction Challenge** (https://criticalminerals.darpa.mil/)
- The proposed system automatically detects line, polygon, point features on the historical map scans, which helps critical mineral assessments
- We thank USGS and DAPAR for providing the high-resolution historical maps and organizing the competition
- We acknowledge MSI and Research Computing for providing powerful computational resources that significantly benefit the research

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