Frontier Artificial Intelligence: Fire Detection Using Synthetic Data, Machine Learning, and Simulated Environments

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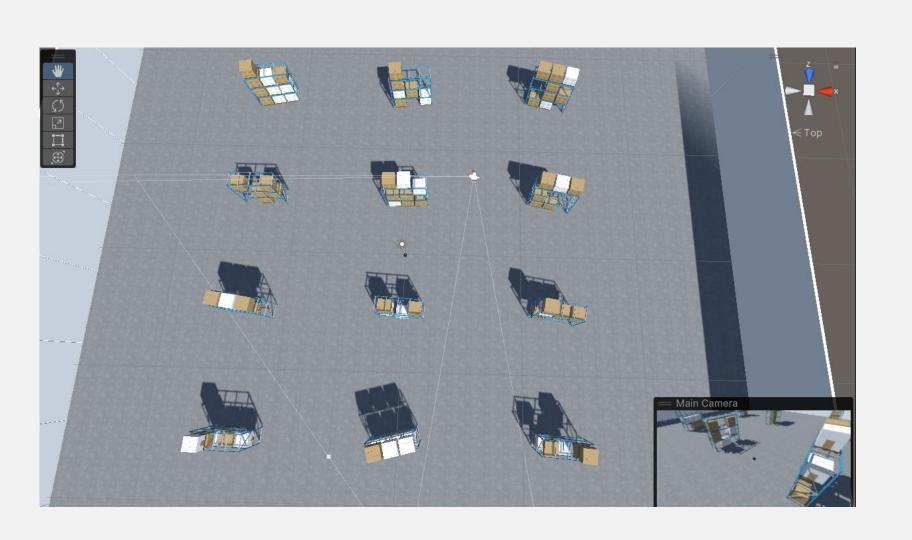
Background: Industrial Fires



Industrial fires, including those in warehouses, are a global concern. In the United States in 2019, there were approximately 37,000 industrial and manufacturing facility fires, as reported by the National Fire Protection Association (NFPA). These fires carry substantial costs, with warehouse fires alone resulting in average losses exceeding \$2 million.

Early detection of such fires is imperative for ensuring worker safety, safeguarding property, and reducing the financial burdens associated with firefighting and property restoration.

- ◆ The project aims to detect fires within warehouses using machine learning techniques for classification
 - ♦ Binary Classification: Enable quick and accurate decision-making
 - ♦ Recognition & Localization: Precisely locate the fire within an image
- ◆ Synthetic fire images were created using Generative AI methods
 - Synthetic data allows for the creation of controlled and diverse fire scenarios, improving model robustness
- ◆ Variable fire types that occur in chemical plants:
 - ♦ Red-fire: Materials containing phosphorus (e.g., certain fertilizers)
 - ♦ Blue-fire: Materials containing copper or lithium (e.g., batteries)





Setup: Dataset & Augmentation

Created a **custom** dataset of **synthetic** images for no-fire, red-fire, and blue-fire. A custom virtual camera sensor was created (Super 16mm, f=14) to **collect** images of (fire) images within the **environment**. Fires were created using Unity's **particle physics** engine.

Dataset Specifics:

- ☐ Sets: no-fire, red-fire, blue-fire
- ☐ Train/Test: 170/70 (Binary Classification)
- ☐ Train/Test/Val: 70:20:10 (Bounding Box Localization)

Synthetic Image Collection Approaches:

- ☐ Fire: Variable size, intensity, rotation angle, distance (depth), height
- ☐ Environment: Ambient lighting variation (night, day, florescent)
- ☐ Torch: TrivialAugmentWide (interpolation)



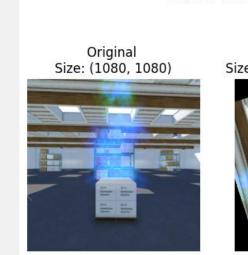
For neural network training, the dataset was bootstrapped with additional data augmentation techniques:

Training Data Augmentation Approaches:

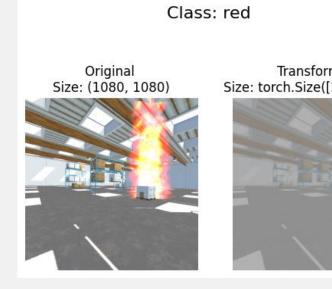
- □ Augment: Flip, rotate: +/- 90°, +/- 15°, saturation, brightness: +/- 25%
- □ Noise: 0~5% of px, Gaussian blur: 0~2.5px, Crop: 0~20% image zoom
- □ Augmentation and Bounding Box Annotation in RoboFlow





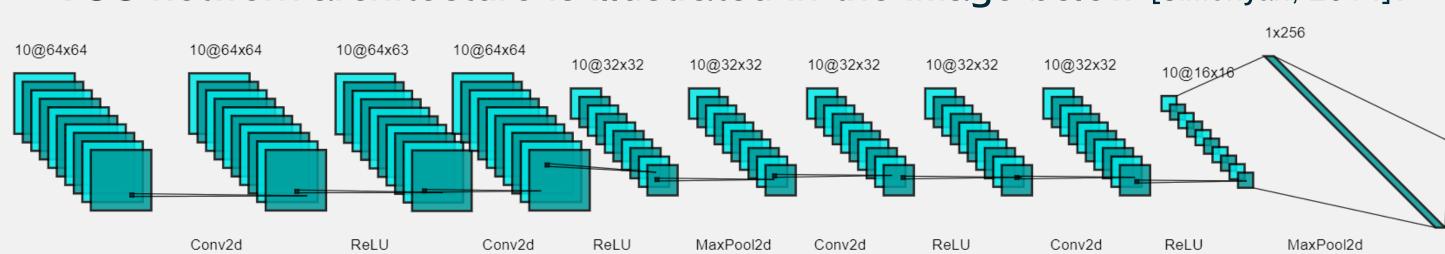






Proposed Solution: Neural Networks

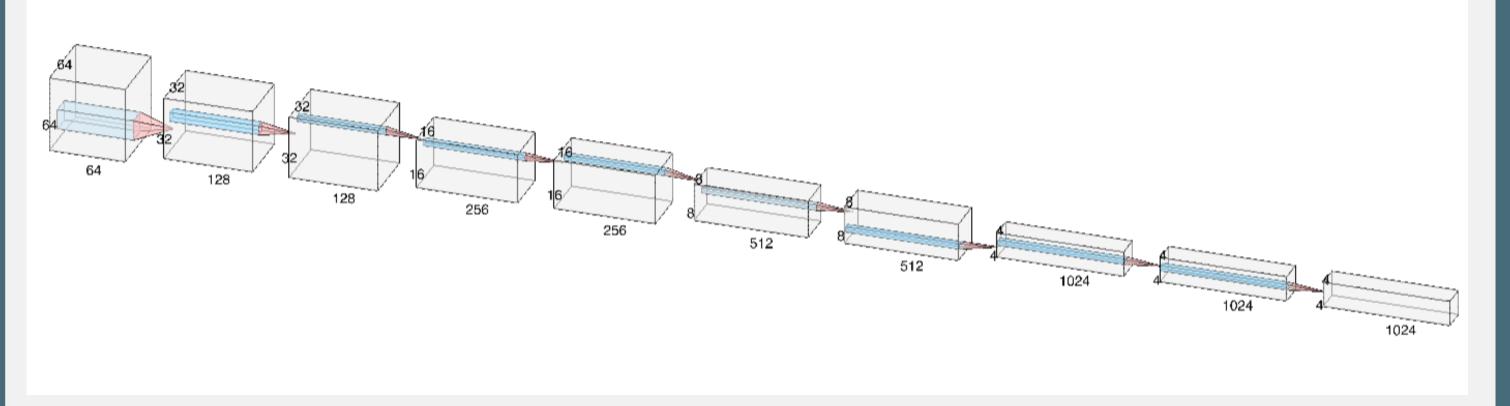
For the binary classification (fire detection), a VGG (Visual Geometry Group) Deep Convolutional Neural Network (DCNN) was constructed. The VGG network architecture is illustrated in the image below [Simonyan, 2014]:



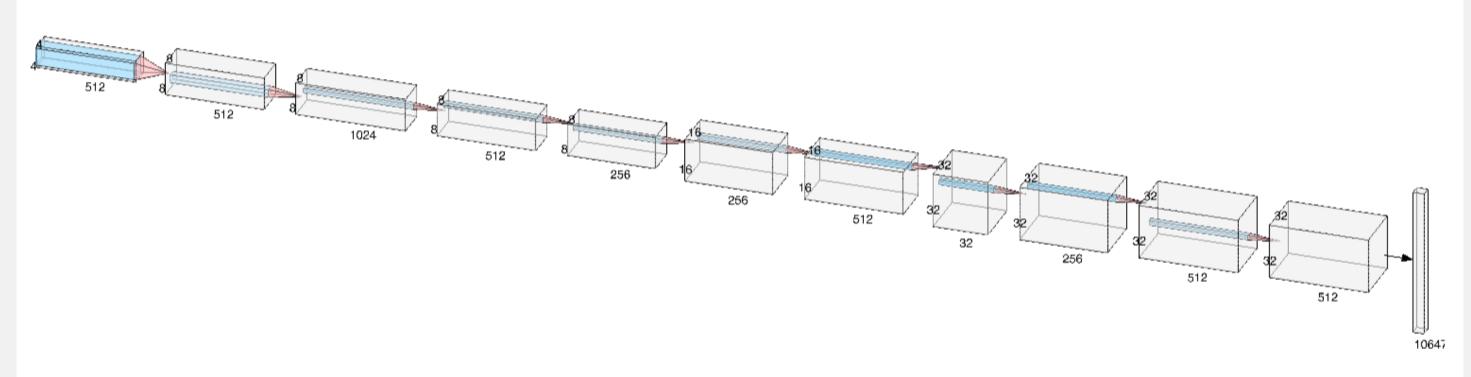
For both architectures:

- ☐ The Adam optimizer was used with Cross Entropy Loss
- □ 20 Training epochs
- □ Variable (dynamic) learning rate (0.01~0.001)
- ☐ Batch size: 64

For the bounding box localization, the YOLO (You Only Look Once) v5 network architecture was used with a backbone and head [Ultralytics, 2021]:



YOLO Backbone



YOLO Head

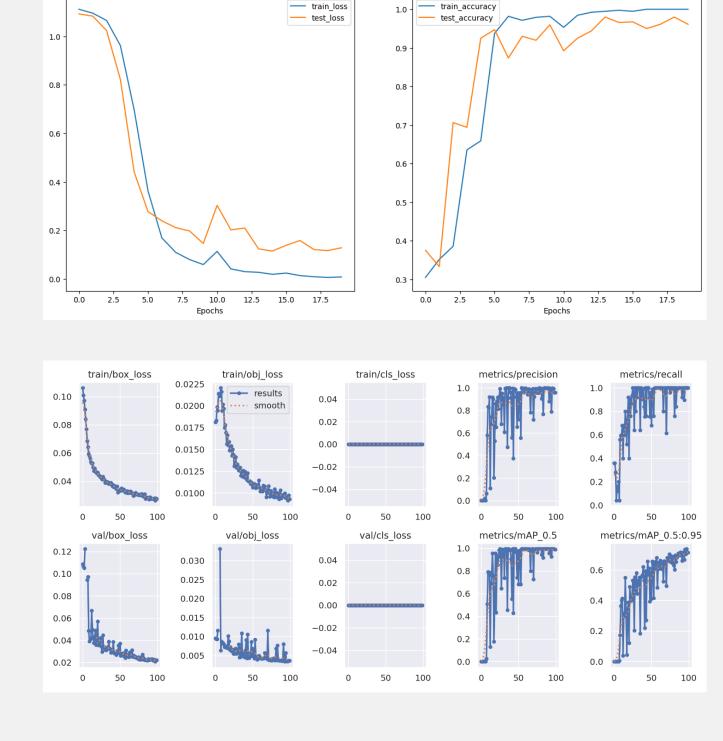
Current Results & Future Work

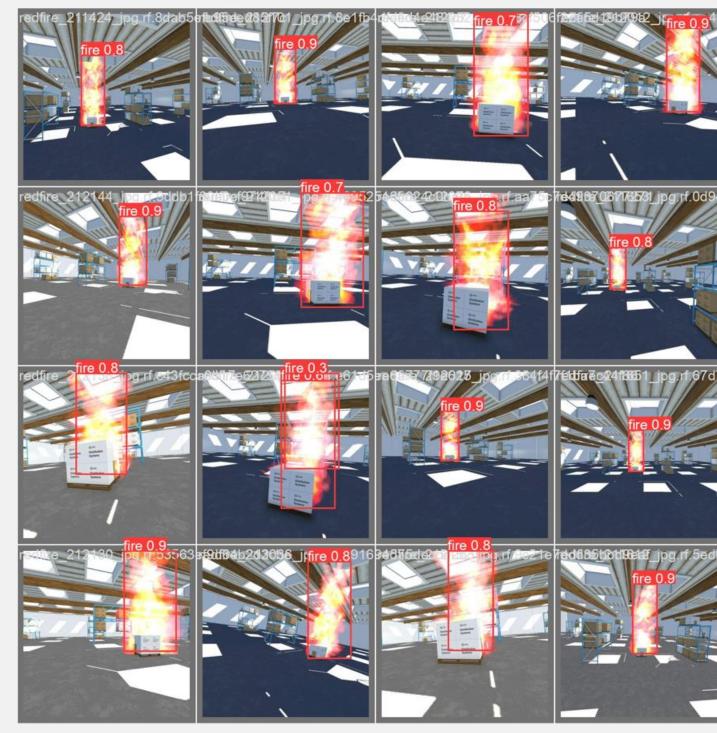
The binary classification approach allows for a quick fire detection, while the bounding box allows for the extraction/derivation of the coordinates for the approximate location of the fire. In a hierarchical decision planner, a robot would be able to quickly identify the existence of a fire, and then report the location. This can be useful for human-in-the-loop disaster mitigation. In the future, robots may be able to autonomously handle fires.

Quantitative Results:

- ☐ Two VGG models were created (below left)
- □ Detection (Classification): Test ACC = 96.11%, loss = 0.12
- □ Localization (Bounding Box): Test Confidence: 71~95% (AVG = 87%)

□ Successfully draws bounding box around ~90% of the fire (discrete)





Future work will include additional hazards that can occur in warehouses, e.g., tools/objects on the floor, puddles of water. Additional environments, such as nuclear reactors, can be created. Furthermore, other image recognition tasks can be included within an updated model (reading pressure gauges, detecting fire extinguishers).







