



THE UNIVERSITY OF
ALABAMA IN HUNTSVILLE

Analysis of AI-Driven UAV Autonomous System Simulation for Use in Hostage Rescue Scenarios

by Daniel Pham, Dr. Vineetha Menon

Overview

- Artificial Intelligence (AI) is part of our lives.
- AI in Combat Search and Rescue (CSAR)
- Hostage situation: urgency
 - Vast, dynamic geographical area
 - Obscured ground vision
- Objectives
 - Gather information on environment quickly and accurately
 - Determine optimal path to hostages and back to safe zones
 - Correctly identify hostages and obstacles
 - Minimal to no casualties
- Can AI systems be trusted to make the right decisions in a hostage rescue scenario?

Introduction

- AI-driven Assistive Autonomous (AI/AA) systems
- Unmanned Aerial Vehicles (UAVs) in defense
- Evading risk for rescuers and soldiers
- Data acquisition and analysis
- Exploration, extraction, and navigation

Objectives

- Map optimal paths to various hostage location points
- Safely navigate optimal paths and extract hostages with minimal to no casualties

Challenges

- Traditional vs newer computer vision architectures
- Data variation
- Confusion and understanding of object features

Simulation Environment

- Unity simulation for CSAR environment
- Human agent and drone agent (AI/AA system)
- 61 participants, split between drone and human agents
- Goal: Rescue all 16 hostages
- Two modes are toggleable
- Limitations
 - Human agent can only navigate along the ground
 - Drones automatically follow a static path

Human-AI/AA System Interaction

Human Mode

- Ground movement limited
- View rotation independent
- Terrain constraints
- Not all hostages visible or reachable

Drone Mode

- Movement in the air
- Sees further
- Easily passes over obstacles
- Cannot yet work in a dynamic environment



Figure 1: Simulation in Human Perspective

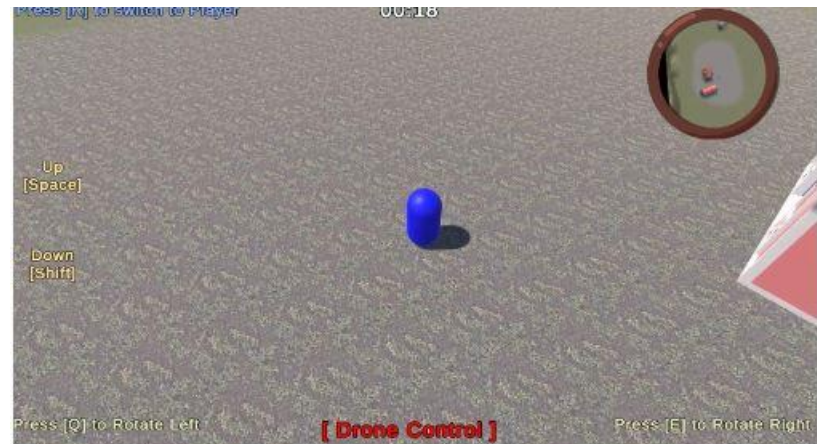


Figure 2: Simulation in Drone Perspective

Proposed PCA-Laplacian-CNN System

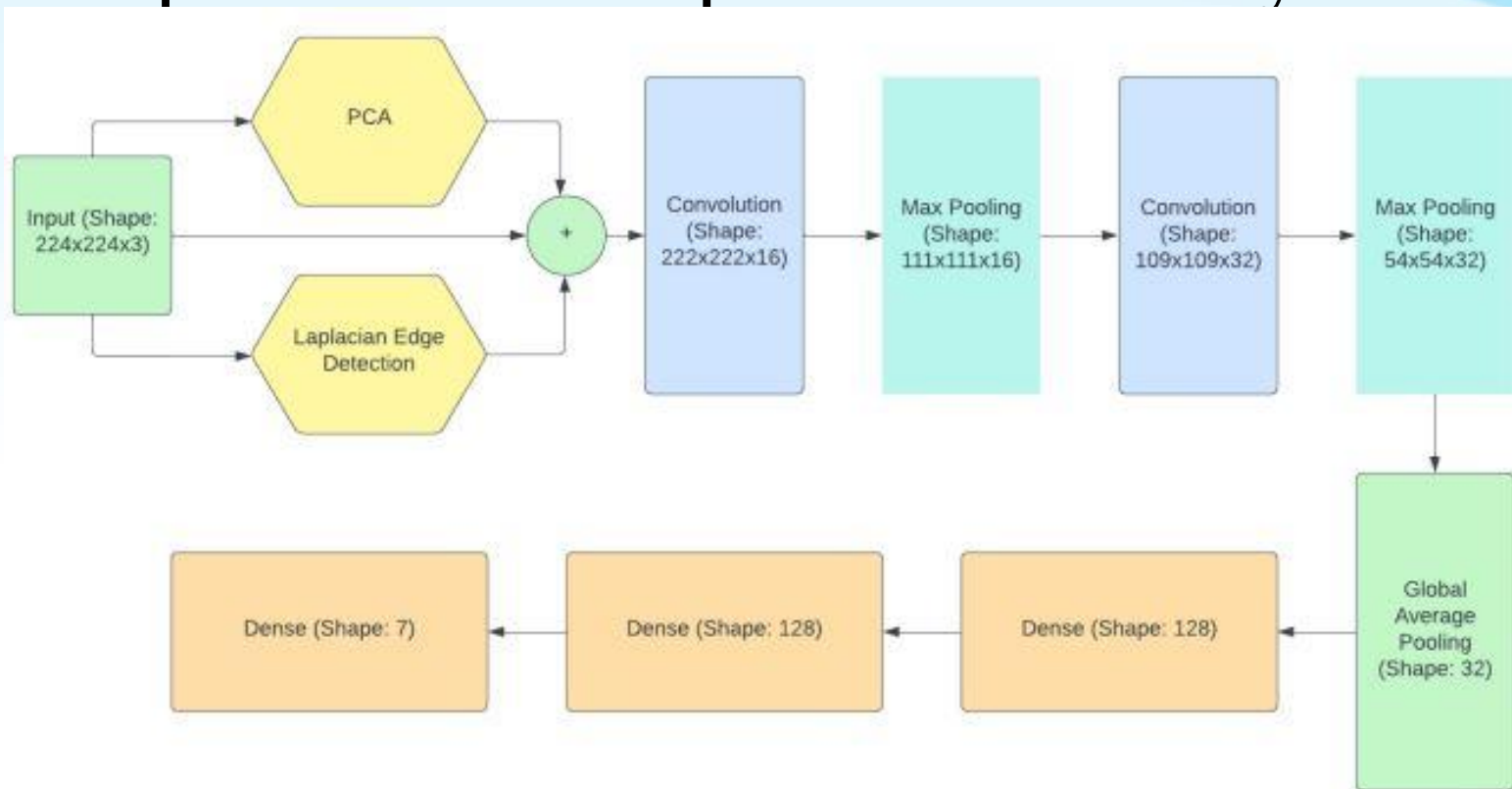


Figure 3. The proposed PCA-Laplacian-CNN drone AI/AA system architecture

- Two convolutional layers
- Two max-pooling layers
- Principal Components Analysis (PCA)
- Edge Detection
 - Laplacian

Data Collection and Preprocessing

- 7 classes, each with 200 images
 - Drones
 - Fountains
 - Grass
 - Hostages
 - Houses
 - Trailers
 - Trees
- Total data: 42000 images
- Batches of 16 images each
- 70:30 train-test split
 - 56% for training
 - 14% for validation
 - 30% for testing

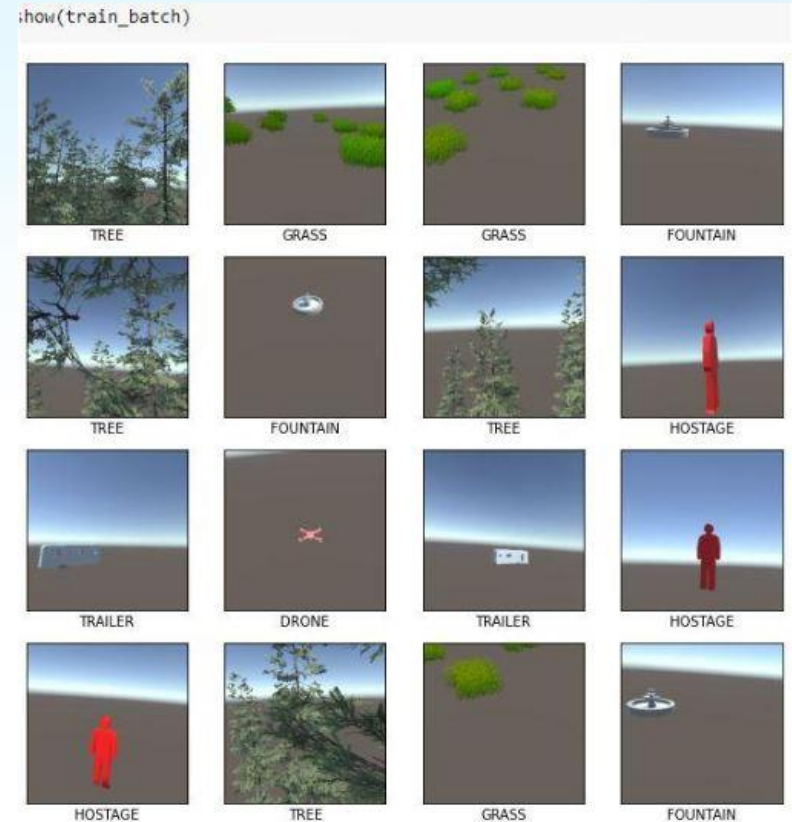


Figure 4: Samples of the images used for training and testing the model

Results and Analysis

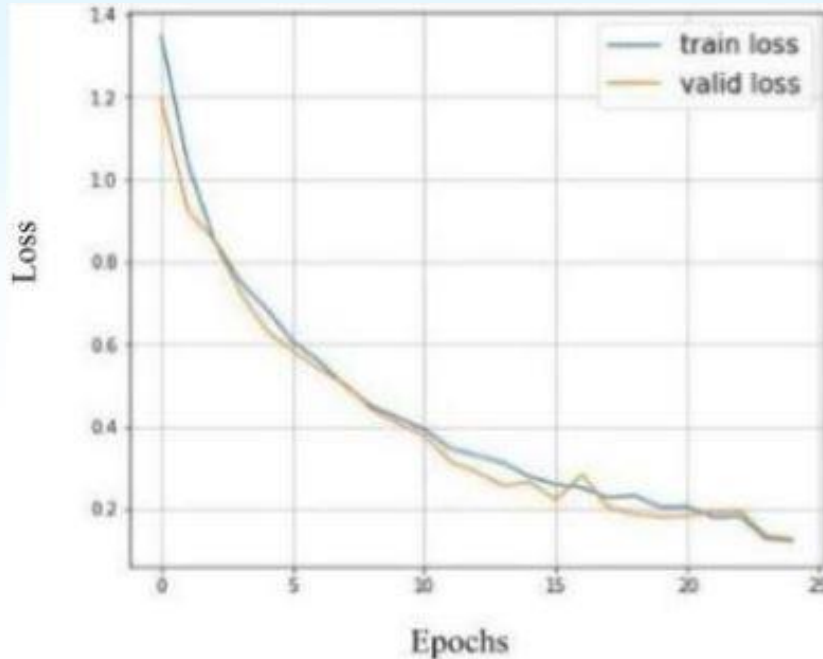


Figure 5a: Training Loss vs Validation Loss

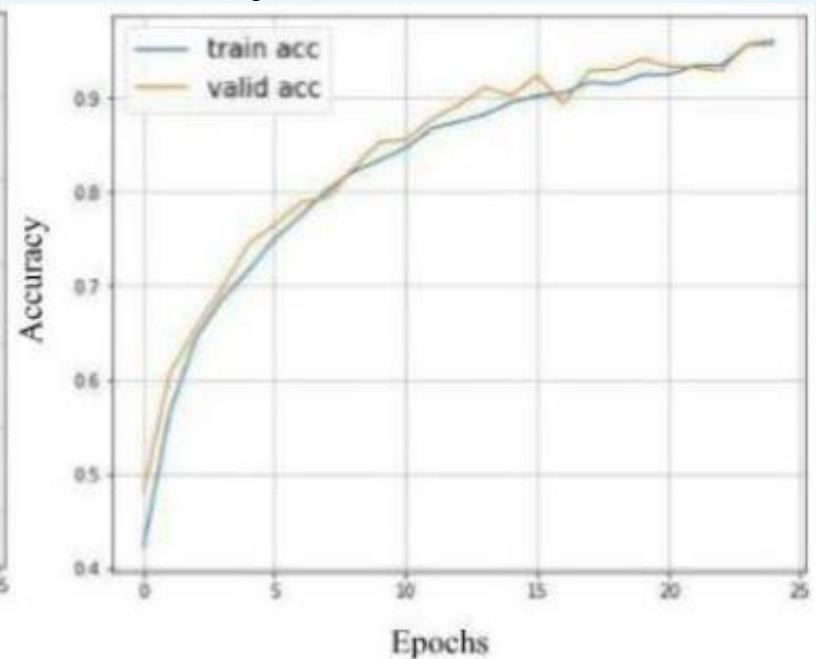


Figure 5b: Training Accuracy vs Validation Accuracy

Loss and accuracy

- Near perfect
- 0.15 Loss
- 95% Accuracy

Accuracies: Overall and Classwise

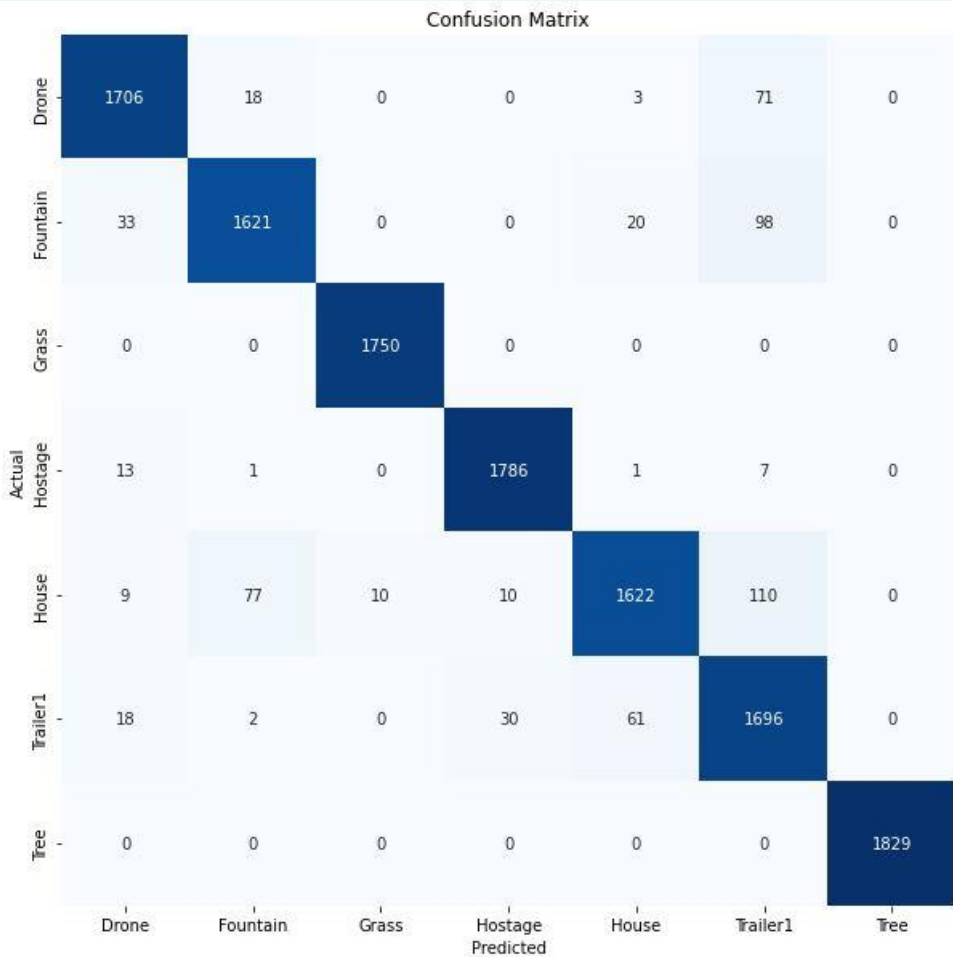


TABLE I
CLASSIFICATION PERFORMANCE OF THE PROPOSED
PCA-LAPLACIAN-CNN MODEL

Class	Precision	Recall	F1-Score
Drone	96%	95%	95%
Fountain	94%	91%	93%
Grass	99%	100%	100%
Hostage	98%	99%	98%
House	95%	88%	92%
Trailer	86%	94%	90%
Tree	100%	100%	100%
Overall Accuracy			95%
Weighted Average	95%	95%	95%

Figure 6: Confusion Matrix of Classwise Accuracies

Conclusion

- Average accuracy: 95%
- Loss is low
- Thus the system proves efficient
- High accuracy identification with little error means the AI system understands the objects of interests and what they look like.
- AI is feasible and trustworthy for hostage rescue scenarios (so far).
 - More realistic data will be used
 - Other architectures will be explored

Thank you!