Explainable Artificial Intelligence framework for Robust Object Detection in Tactical Unmanned Vehicles (XAI-UAV)

Review - 1

Under the Guidance of

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VIT-AP UNIVERSITY

Proposal Report

Capstone Project Proposal Report
(Individual Report)

Guide Approval (initials/date):	Deepasikha Mishra	26/8/25

CAP4001– Capstone Project Proposal Report

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Programme	**B.Tech, Computer Science and Engineering - AIML**
Semester/Year	**FallSem 2025-26**
Guide(s)	**Dr. Deepasikha Mishra**
Project Title	**XAI-UAV: Explainable Artificial Intelligence Framework for Robust Object Detection in Tactical Unmanned Aerial Vehicles**

Team Composition:

Reg. No	Name	Major	Specialization
22BCE7331	Konakalla Rishitha	CSE	AIML
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Motivation

- In high-stakes UAV applications like surveillance & defense, AI must not only be fast, it must be explainable
- Current object detection models used in drones (e.g., YOLO) are accurate, but behave like black boxes
- Lack of transparency reduces trust, limits adoption, and poses risks in human-AI decision-making
- We are motivated to bridge this gap by building a real-time, interpretable AI system for UAVs
- Our solution merges model optimization (DetDSHAP) with visual explanations (Grad-CAM, SHAP) — ensuring both performance and accountability

Objectives

- Identify and address the lack of explainability in UAV-based object detection systems
- Optimize deep learning models (YOLOv5/YOLOv8) for real-time inference on edge devices (e.g., Jetson, FPGA)
- Apply DetDSHAP pruning to reduce model size while preserving performance and interpretability
- Integrate explainability tools (Grad-CAM, SHAP, Saliency Maps) into the UAV inference pipeline
- Build a ground station interface that visualizes detections alongside their explanations
- Evaluate both detection accuracy (mAP, F1) and explanation quality (fidelity, stability)

Hypothesis

- We hypothesize that DetDSHAP-guided pruning can produce a lightweight YOLO model that is both accurate and interpretable
- We propose that integrating XAI methods (Grad-CAM, SHAP, Saliency Maps) with the deployed model will enable real-time visual explanations onboard UAVs
- We believe this combination will allow UAV operators to understand and trust AI decisions without compromising performance
- Our pipeline will maintain detection accuracy while also delivering explanation fidelity and stability, bridging the gap between efficiency and transparency

Problem Survey

State of the Art

- UAV object detection: *VisDrone*, *UAVDT* benchmarks; YOLOv5/YOLOv8 widely adopted for aerial vision.
- Edge AI deployments: *Jetson Nano/Orin* enable onboard inference but limited by resource constraints.
- XAI methods (Grad-CAM, SHAP, Saliency Maps) are established in medical and NLP domains, rarely extended to UAV detection.

Limitations Identified

- Existing UAV research optimizes models for speed but overlooks interpretability.
- No standardized inclusion of fidelity/stability metrics alongside accuracy.
- Edge pruning is often magnitude-based, risks accuracy drop and ignores explainability.

Premise of Proposal

- Introduce DetDSHAP-guided pruning: interpretable model compression.
- Integrate real-time explainability engine in UAV object detection pipeline.
- Deliver trustworthy, operator-validated UAV AI that balances accuracy, efficiency, and transparency.

Subject Knowledge

Object Detection Models

- YOLO family: **single-shot, real-time detection**
- Trained on **UAV-specific datasets** (VisDrone, UAVDT)
- Balancing **accuracy (mAP)** vs. **efficiency (FPS, latency)** is critical for UAV hardware

Optimization

- **DetDSHAP Pruning**:
  - Uses Shapley values to rank neuron importance
  - Retains interpretability while reducing parameters
- **Deployment Workflow**:
  - PyTorch (training) → ONNX (intermediate format) → TensorRT (.engine model)
  - Runs efficiently on Jetson/FPGA hardware

Subject Knowledge

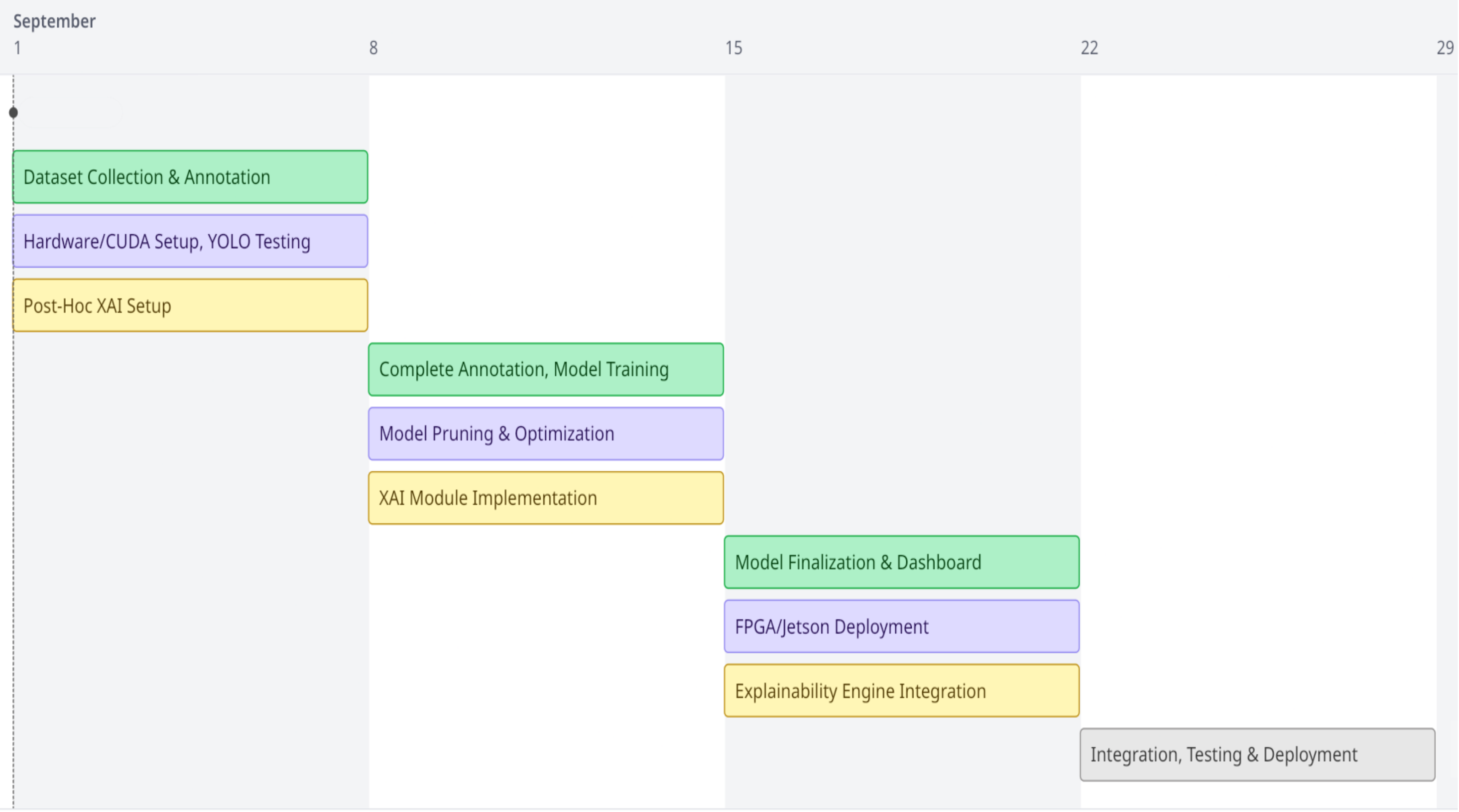
Evaluation Framework

- **Accuracy:** mAP, F1-score
- **Efficiency:** Latency per frame, FPS, GPU/Memory utilization
- **Interpretability:**
  - *Fidelity*: explanation truly reflects model's reasoning
  - *Stability*: explanations consistent for similar UAV inputs

Explainability Methods

- **Grad-CAM:** Highlights *which regions in feature maps* drive detections
- **Saliency Maps:** Pixel-level sensitivity showing *why detection confidence changes*
- **SHAP:** Quantifies *numerical importance* of image regions to predictions

Time Plan


September
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Dataset Collection & Annotation
Hardware/CUDA Setup, YOLO Testing
Post-Hoc XAI Setup
Complete Annotation, Model Training
Model Pruning & Optimization
XAI Module Implementation
Model Finalization & Dashboard
FPGA/Jetson Deployment
Explainability Engine Integration
Integration, Testing & Deployment

Thank you!

Team members:

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