

Camouflage Reveal Neural Network App (CaReNN)

Nathan Ogden, Lilly Redmond, Olivia Tucker, Christian Boldin, Barrett Peterson
Mentor: Dr. David Coe, Associate Professor, Electrical and Computer Engineering, UAH

The Need: Military personnel require improved detection of camouflaged threats in complex environments. Advancements in camouflage make threats hard to detect.

The Solution: CaReNN is a smartphone-based system that identifies camouflaged objects in real-time, using YOLOv8 and operating offline for security purposes and portability.

Status: The CaReNN model is trained to a Mean Average Precision (mAP) of 70% and deployed on the Google Pixel 9 Pro. Object detection is now operational, running in real time using a TensorFlow Lite model for on-device camouflage detection.



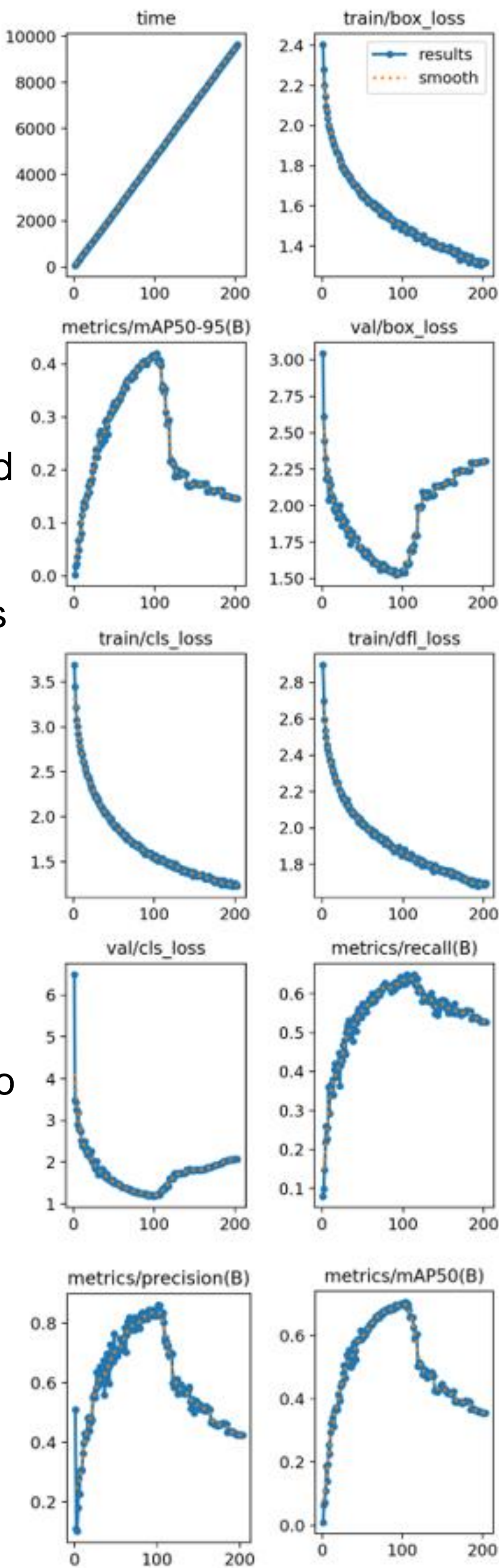
Current Results:

Model Performance: Achieved 70% mAP @ 50% IoU, trained on 5,000+ images across diverse environments.

App Functionality: Has live camera feed and a login page for extra security.

App Deployment: Application installed on Google Pixel 9 Pro

Conclusion: The CaReNN project has successfully developed and integrated an Android Studio application and a trained YOLOv8-based camouflage detection model into a functional real-time detection system. The application now performs on-device inference, enabling live camouflage detection through a smartphone camera feed. Datasets used in training include military-specific personnel in addition to common types of camouflage in an effort to improve the model’s performance and relevance in field scenarios. This project serves as a successful proof of concept for deploying camouflage detection models on edge devices, demonstrating the practicality and effectiveness of real-time, on-device object recognition.



Requirements

Marketing	Engineering
M1: Detect camouflaged objects in real-time.	E1: The system must achieve a camouflage detection Mean Average Precision (mAP) of at least 70% at a 50% Intersection over Union (IoU) threshold, tested on 500+ objects in diverse environments.
M2: Work effectively in different environment conditions.	E2: Train in 5,000+ images (≥ 640 x 640 resolution).
M3: Mobile app functionality	E3: Include live video with ≤1s delay at ≥15 FPS. E4: Include a confidence slider for detection sensitivity. E5: Highlight detected objects with bounding boxes.

Acknowledgements and References

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Timing Diagram

