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2023/24

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Objective

- **Camera-based detection and tracking for drones.**
- **System reliability in dynamic environments.**
- **Real-time performance (<35ms).**
- **Detect and track other drones onboard.**
- **High accuracy and efficiency.**

Existing work

- **GPS limitations:** Inaccurate in urban areas, misses crucial data captured by onboard cameras.
- **Missed opportunities:** GPS reliance overlooks vital information, especially in GPS-interfered regions.
- **Urban challenges:** GPS inadequacies accentuated in urban settings, underscoring the need for onboard camera solutions.



Dataset

- **Extensive dataset:** Over 10,000 drone images sourced from diverse online and video sources.
- **Varied content:** Captured drones at various distances, from different vendors, ensuring comprehensive coverage.
- **Manual annotation:** More than half of the dataset manually annotated for high-quality labeled data.
- **Largest on Kaggle:** Recognized as one of the largest drone dataset of drones on Kaggle, offering unmatched scale and diversity.
- **Quality assurance:** Rigorous quality control ensures dataset integrity and reliability.
- **Versatile applications:** Suitable for various computer vision tasks beyond drone detection.



Nature Background



Urban Background



Drone Details



Hard To Find Drone

Detection & Tracking

Detector: YOLOv8

- **Training details:** Trained for 20 epochs using a dataset split of 70% for training, 15% for testing, and 15% for validation.
- **Performance metrics:** Achieved 94% precision and 92% recall.
- **Optimization attempts:** Despite efforts to minimize model size through pruning, quantization, and backbone modifications, real-time inference speeds on edge hardware were not attained.

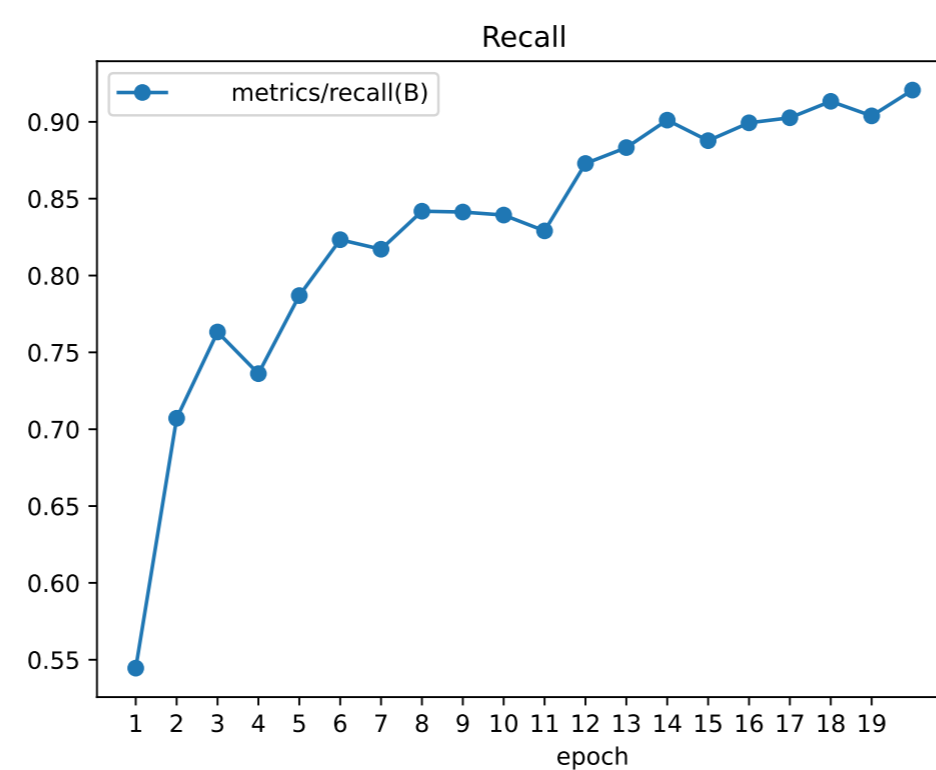
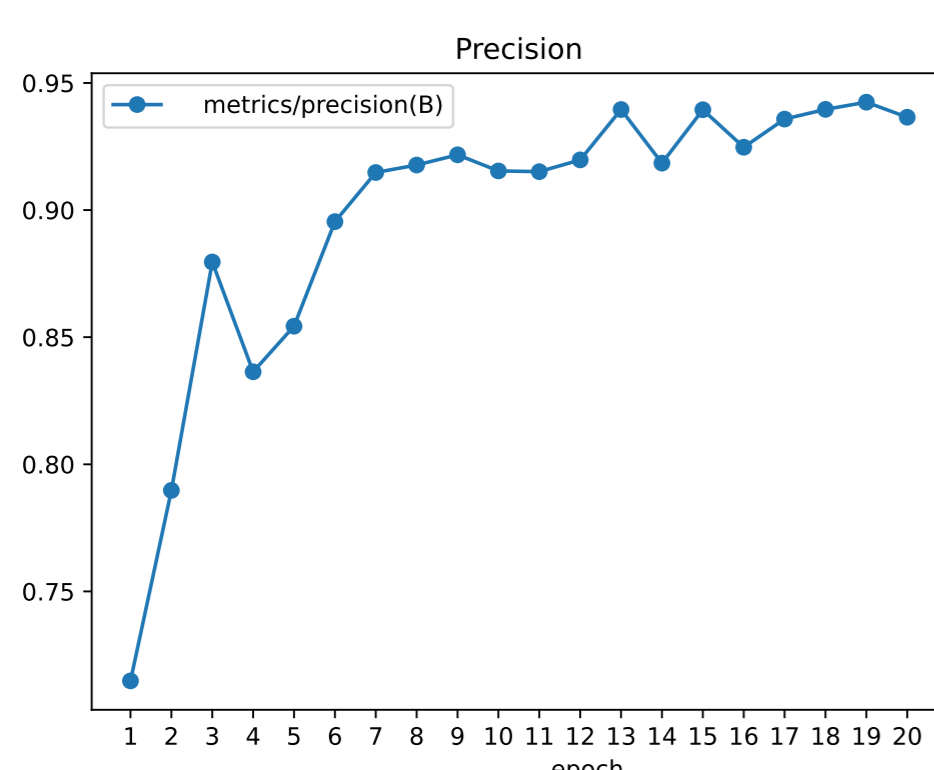


Tracker: MOSSE, KCF, TLD, CSRT, VIT

- **Purpose:** Implemented to compensate for onboard detection limitations and maintain tracking during slow detection speeds.
- **Selection criteria:** Different trackers were tested based on their ability to fill detection gaps and their inference speed compared to the detector.
- **Evaluation metrics** (tested on a subset of TrackingNet):
 - TLFF (Tracking Length to First Failure): Measures the number of frames until the first failure in tracking.
 - RL (Recovery Length): Indicates the number of frames required for the tracker to recover after a failure.
 - RF (Recovery Failure Percentage): Percentage of failed recovery attempts.
 - UNR (Unnecessary Full Sequence Tracking Percentage): Percentage of tracking sequences that were fully tracked without failure.

[ms/per frame]	Raspberry Pi 4	Nvidia Jetson Nano	Intel Core i7-9750HQ	NVIDIA GTX 1660ti
PyTorch	1244	316	51	7
ONNX	600	X	47	X

YOLOv8 Detection Speeds On Various Platforms and Inference Engines

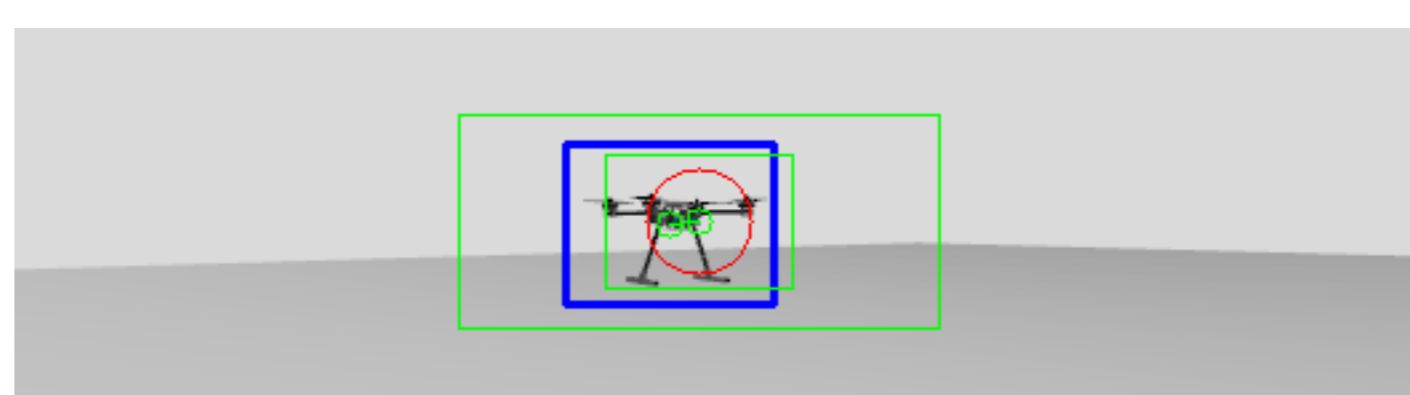


	TLFF	RL	RF	UNR	Speed [ms/per frame]
MOSSE	127.12 (26.67%)	32.71 (6.85%)	46%	14%	0.183
KCF	158.01 (33.34%)	31.66 (6.57%)	39%	16%	1.186
TLD	41.67 (8.66%)	27.08 (5.81%)	14%	2%	21.612
CSRT	188.72 (39.69%)	21.05 (5.68%)	18%	19%	21.482
VIT	228.69 (48%)	17.75 (4%)	6%	28%	9.230

Evaluation of Trackers on TrackingNet; mean num. of frames is 478

Testing in Simulation

- **Testing Environment:** Simulator (Gazebo) with ROS2 and PX4 drone stack integration.
- **Surveillance Implementation:** Utilized a simple box minimization algorithm for proof of concept.
- **Control Algorithm:** Drone bounding box utilized from detection is used for movement in YZ plane; bounding box size employed for X-axis movement.



Following Drone Perspective

