

Boxing Punch Detection using YOLOv7

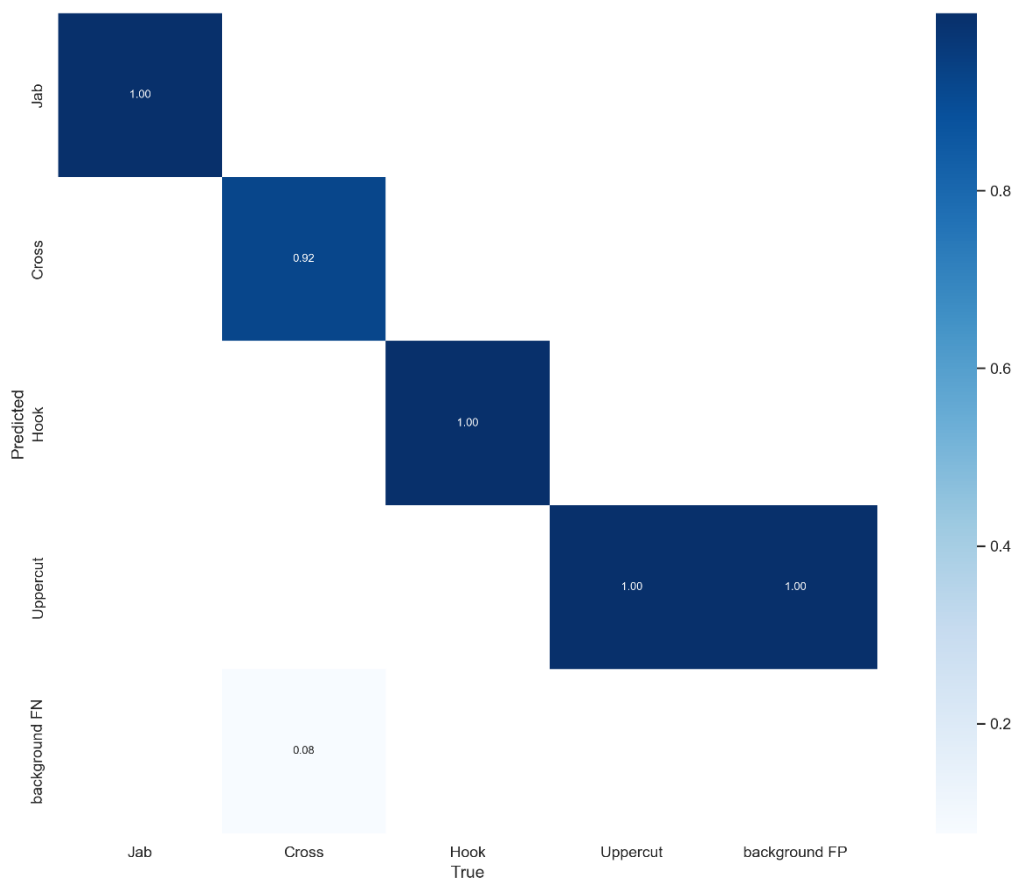
Project Links

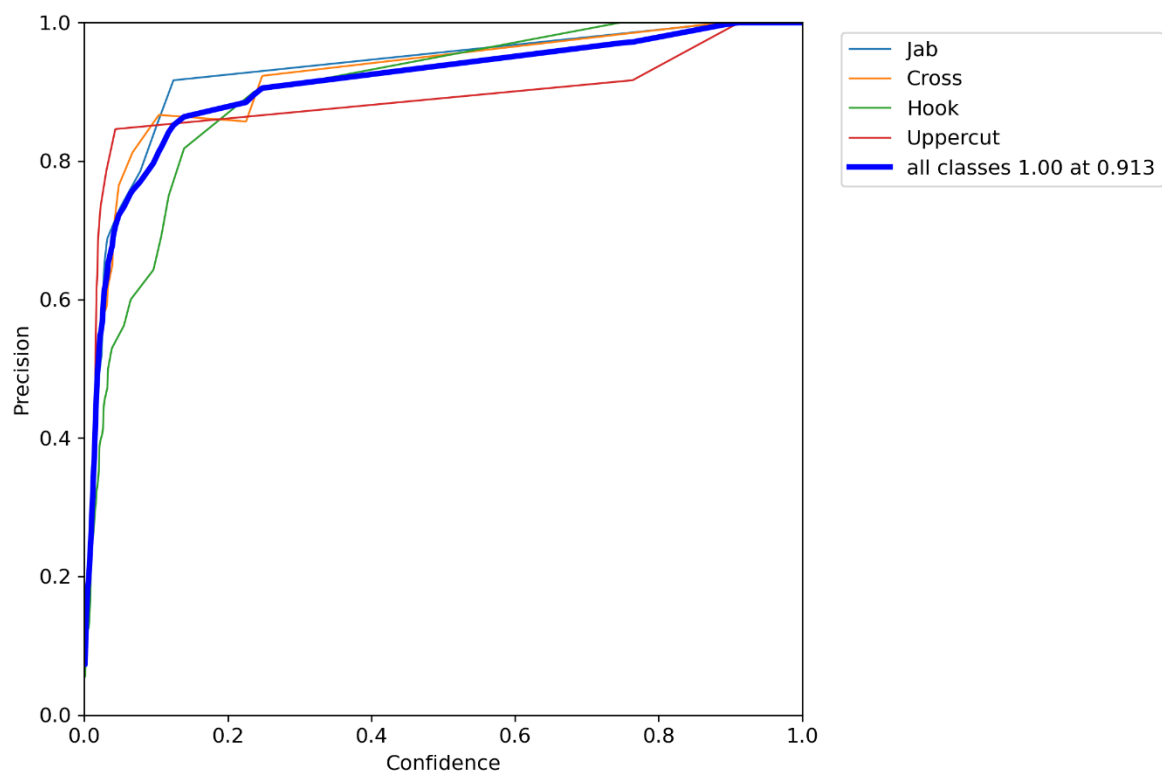
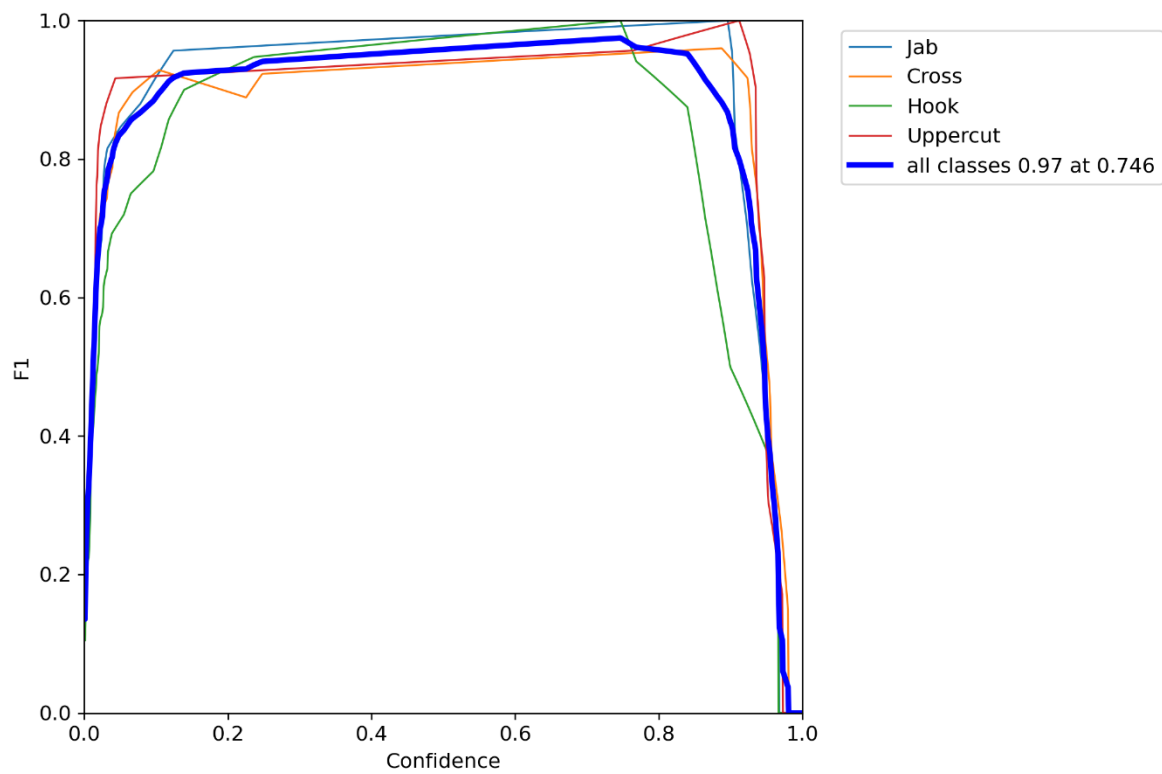
- Project Readme: [Link](#)
- Full Project: [GoogleDrive Link](#)
- Trained Model Weights: [Weights](#)
- Training Dataset: [Dataset](#)
- Test Results: [Detections Results](#)

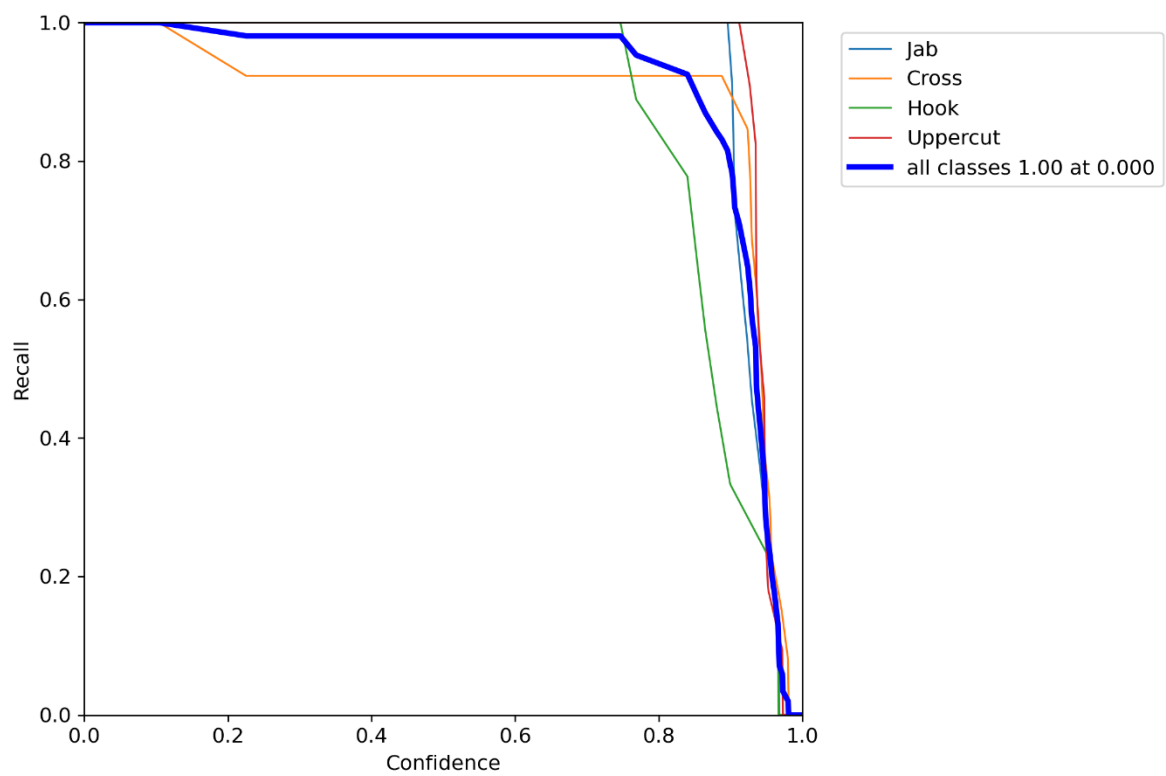
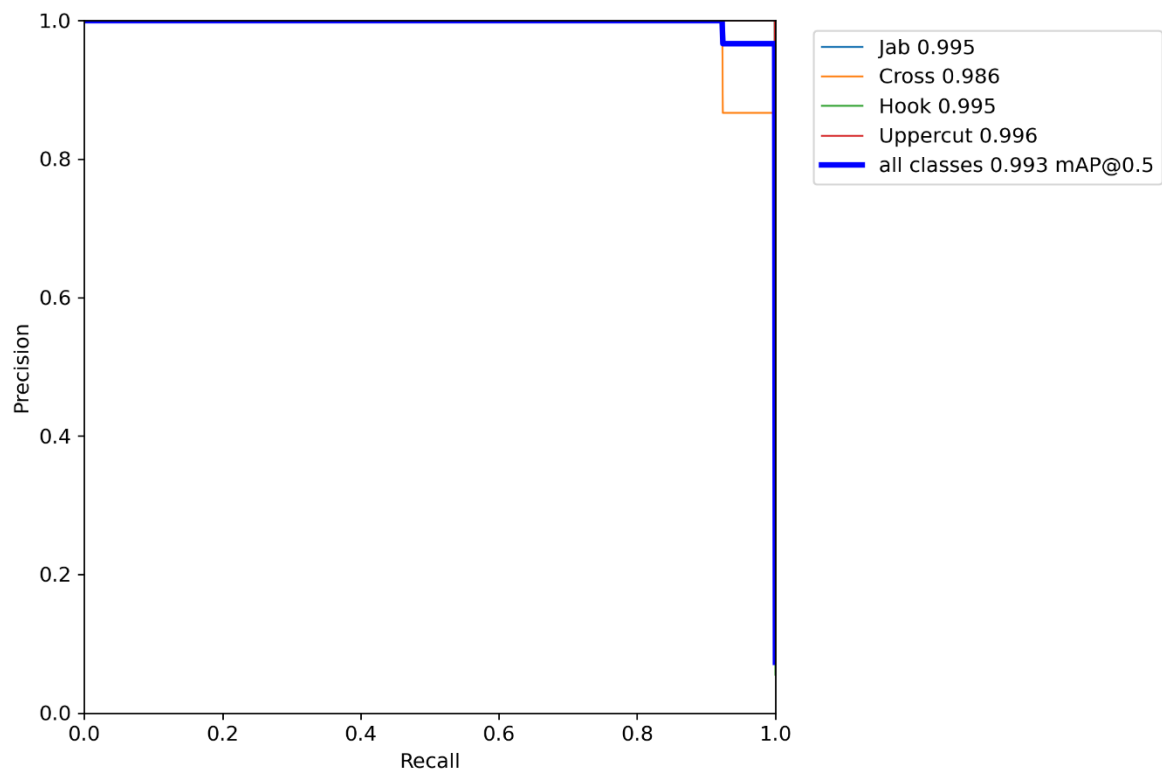
Summary

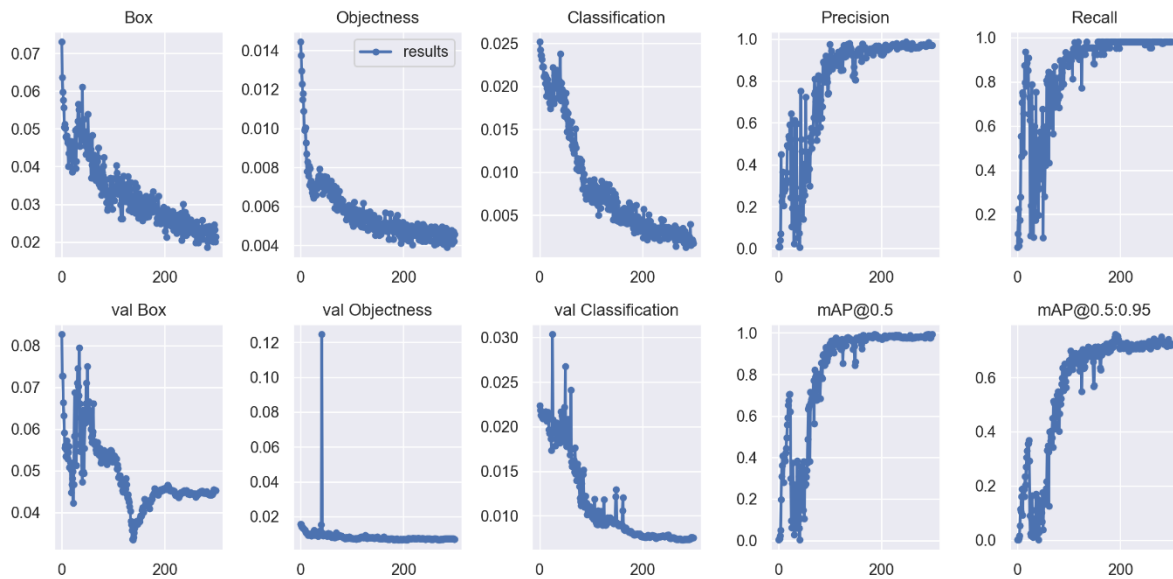
This implementation of YOLOv7 for boxing punch detection demonstrates exceptional performance across all key metrics. The model successfully classifies four punch types (jab, cross, hook, uppercut) with high precision and recall. After 300 epochs of training, the model achieved a mean Average Precision (mAP@0.5) of 0.993, making it suitable for real-world boxing analysis applications.

Training Metrics/Performance Graphs:









1. Model Architecture and Training

1.1 Training Configuration

- Base Architecture: YOLOv7
- Training Duration: 300 epochs
- Input Resolution: 640x640
- Classes: 4 (jab, cross, hook, uppercut)
- Hardware: NVIDIA GPU A100
- Batch Size: 16

1.2 Training Convergence

The training process showed consistent improvement across all metrics:

- Box loss decreased from 0.07 to 0.02
- Objectness loss stabilized at 0.004
- Classification loss reached 0.003
- No signs of overfitting observed in validation metrics

2. Performance Metrics

2.1 Classification Accuracy

Per-class performance metrics:

- Jab: 0.995 mAP
- Cross: 0.986 mAP
- Hook: 0.995 mAP
- Uppercut: 0.996 mAP

The confusion matrix reveals minimal cross-class confusion, with only the Cross class showing slight confusion (0.08) with background detections.

2.2 Detection Quality

- mAP@0.5: 0.993
- mAP@0.5:0.95: ~0.8
- Precision at 0.913 confidence: 1.00
- Recall at base threshold: 1.00

These metrics indicate robust detection capabilities across varying intersection-over-union (IoU) thresholds.

3. Detailed Analysis

3.1 Precision-Recall Characteristics

The model maintains high precision (>0.95) across all classes until very high recall values, indicating:

- Reliable punch classification
- Minimal false positives
- Robust performance across different punch styles and angles

3.2 Confidence Thresholds

Analysis of confidence thresholds reveals optimal operating points:

- General detection: 0.75-0.80 confidence threshold
- High-precision requirements: 0.913 threshold
- Maximum recall: 0.5 threshold

3.3 Training Stability

The training curves demonstrate stable convergence:

- Smooth loss reduction across all components
- Consistent validation metrics
- No significant oscillations after epoch 200

4. Technical Insights

4.1 Model Behavior

The model shows particularly strong performance in:

- Distinguishing between similar punch types (e.g., jab vs. cross)
- Maintaining accuracy across different viewing angles

- Handling varying boxing styles and speeds

4.2 Operating Points

For optimal real-world performance, we recommend:

- Confidence Threshold: 0.75
- NMS IoU Threshold: 0.45
- Input Resolution: 640x640 (native training resolution)

5. Limitations and Future Work

5.1 Current Limitations

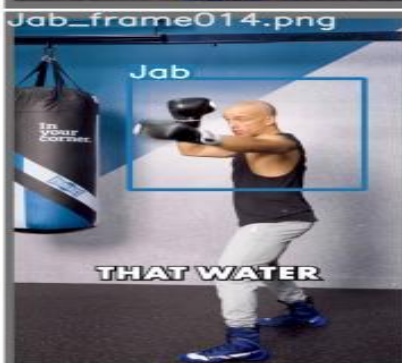
- Cross punch detection shows slightly lower precision (0.92)
- Performance on extreme angles not fully validated
- Real-time performance needs further optimization

5.2 Recommended Improvements

1. Data augmentation focusing on Cross punch variations
2. Integration of temporal information for combo detection
3. Model quantization for faster inference
4. Implementation of punch speed calculation

Test Results:

Labels:



Predictions:



Conclusion

The YOLOv7-based boxing detection system demonstrates production-ready performance with exceptional accuracy across all punch types. The model's robust metrics and stable

training behavior make it suitable for real-world boxing analysis applications. With minimal fine-tuning of confidence thresholds, the system can be optimized for specific use cases requiring either higher precision or recall.

For deployment, we recommend the 0.75 confidence threshold as it provides the best balance between precision and recall while maintaining real-time performance capabilities. Future work should focus on expanding the system to detect combinations and implement speed calculations while maintaining the current high accuracy levels.