ABSTRAK

Bulu tangkis merupakan olahraga berintensitas tinggi dengan *shuttlecock* berukuran kecil dan bergerak cepat, sehingga keputusan posisi jatuhnya shuttlecock (in/out) dapat menimbulkan kesalahan saat mengandalkan pengamatan manual hakim garis. Penelitian ini menerapkan metode YOLOV8n untuk deteksi otomatis status in/out shuttlecock secara efisien. Metode ini mendeteksi dua kelas objek, yaitu shuttlecock dan garis lapangan, menggunakan video pertandingan bulu tangkis untuk memperkuat keputusan wasit, dan mendukung sistem penilaian berbasis data.

Dataset diperoleh dari Roboflow Universe sebanyak 2.730 citra (.JPG) yang dianotasi manual menjadi dua kelas (*shuttlecock* dan garis lapangan). Tahap *preprocessing* meliputi konversi video ke frame, pemberian label, dan pembagian data menjadi 2.030 *training* dan 700 *validation*. Model YOLOV8n dilatih menggunakan optimizer AdamW dan hyperparameter (epoch, batch size, imagesize) lalu dievaluasi melalui metrik Precision, Recall, Average Precision (AP), dan mAP50. Hasil evaluasi menunjukkan deteksi garis lapangan (Precision 97,9% Recall 99,8%), sedangkan deteksi shuttlecock (Precision 85,6%; Recall 75,9%). Nilai AP garis lapangan (99,5%) dan shuttlecock (81,4%), dengan total mAP50 sebesar 90,45%.

Penelitian ini berhasil menerapkan metode YOLOV8n sebagai deteksi otomatis *shuttlecock in/out*. Namun, peningkatan masih diperlukan pada deteksi shuttlecock melalui perluasan dataset, peningkatan kualitas video, penyesuaian *hyperparameter*, dan penerapan varian model lain (YOLOv8s atau YOLOv8m) untuk meningkatkan akurasi dan konsistensi dalam deteksi berbagai kondisi pertandingan.

Kata Kunci: Bulu tangkis, *Computer vision*, Deteksi *Shuttlecock*, *Deep learning*, *In/Out Detection* YOLOV8.

ABSTRACT

Badminton is a high-intensity sport with a small and fast-moving shuttlecock, making in/out judgments prone to human error when relying solely on manual observation by line judges. This study applies the YOLOV8n method for efficient automatic detection of shuttlecock in/out status. The method detects two object classes—shuttlecock and court lines—from badminton match videos to support umpire decisions and enable data-driven scoring systems.

The dataset was obtained from Roboflow Universe, consisting of 2,730 JPG images manually annotated into two classes (shuttlecock and court lines). The preprocessing stage included video-to-frame conversion, labeling, and data splitting into 2,030 for training and 700 for validation. The YOLOV8n model was trained using the AdamW optimizer and evaluated using Precision, Recall, AP, and mAP50 metrics.

Evaluation results show that court line detection achieved high performance (Precision 97.9%, Recall 99.8%), while shuttlecock detection achieved (Precision 85.6%, Recall 75.9%). The Average Precision (AP) values reached 99.5% for court lines and 81.4% for shuttlecock, resulting in an overall mAP50 of 90.45%.

This study successfully implemented the YOLOV8n method for automatic shuttlecock in/out detection in badminton. However, improvements are still needed for shuttlecock detection through dataset expansion, video quality enhancement, hyperparameter optimization, and the application of larger model variants (YOLOv8s or YOLOv8m) to increase accuracy and consistency under various match conditions.

***Keywords**: Badminton, Computer vision, Deep learning, In/Out Detection, Shuttlecock Detection, YOLOV8.*