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YOLO MODEL DETECTION OF STUDENT NEATNESS BASED ON DEEP LEARNING: A SYSTEMTIC LITERATURE REVIEW

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Abstract— *Maintaining proper student neatness (uniform compliance, grooming standards, and posture) is essential for fostering disciplined learning environments. While traditional monitoring methods are labor-intensive and subjective, computer vision-based solutions leveraging You Only Look Once (YOLO) architectures offer promising alternatives. The objective of this study is to evaluate YOLO optimization techniques for student neatness detection, identify key challenges, and propose relevant future research directions. This systematic review evaluates 28 recent studies (2021-2024) to analyze optimization techniques for YOLO models in student neatness detection applications. Key findings demonstrate that attention-enhanced variants (e.g., YOLOv10-MSAM) achieve 87.0% mAP@0.5, while pruning and quantization methods enable real-time processing (50-130 FPS) on edge devices like Jetson Orin. The analysis reveals three critical challenges: (1) occlusion handling in crowded classrooms (10-15% false negatives), (2) lighting/background variability, and (3) ethical concerns regarding facial recognition. Emerging solutions include hybrid vision-language models for explainable detection and federated learning for privacy preservation. The review proposes a taxonomy of optimization approaches categorizing architectural modifications (attention mechanisms, lightweight backbones), data augmentation strategies (GAN-based synthesis), and deployment techniques (TensorRT acceleration). Future research directions emphasize multi-modal sensor fusion and domain adaptation for cross-institutional generalization. This work provides educators and AI developers with evidence-based guidelines for implementing automated neatness monitoring systems while addressing practical constraints in educational settings.*

Keywords*: computer vision, deep learning, real-time detection, student neatness, YOLO.*

Intisari— *Mempertahankan kerapian siswa yang tepat (kepatuhan seragam, standar penataan, dan postur) sangat penting untuk menciptakan lingkungan belajar yang disiplin. Sementara metode pemantauan tradisional membutuhkan banyak tenaga kerja dan bersifat subjektif, solusi berbasis visi komputer yang memanfaatkan arsitektur You Only Look Once (YOLO) menawarkan alternatif yang menjanjikan. Tujuan dari penelitian ini adalah untuk mengevaluasi teknik optimasi YOLO untuk deteksi kerapian siswa, mengidentifikasi tantangan utama, dan mengusulkan arah penelitian yang relevan di masa depan. Tinjauan sistematis ini mengevaluasi 28 studi terbaru (2021-2024) untuk menganalisis teknik optimasi untuk model YOLO dalam aplikasi deteksi kerapian siswa. Temuan utama menunjukkan bahwa varian yang ditingkatkan perhatian (misalnya, YOLOv10-MSAM) mencapai 87,0% mAP@0.5, sementara metode pemangkasan dan kuantisasi memungkinkan pemrosesan waktu nyata (50-130 FPS) pada perangkat edge seperti Jetson Orin. Analisis ini mengungkapkan tiga tantangan kritis: (1) penanganan occlusion di kelas yang ramai (10-15% negatif palsu), (2) variasi pencahayaan/background, dan (3) masalah etis terkait pengenalan wajah. Solusi yang muncul termasuk model hibrida visi-bahasa untuk deteksi yang dapat dijelaskan dan pembelajaran terfederasi untuk perlindungan privasi. Tinjauan ini mengusulkan taksonomi pendekatan optimasi yang mengkategorikan modifikasi arsitektur (mekanisme perhatian, tulang punggung ringan), strategi augmentasi*

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data (sintesis berbasis GAN), dan teknik penerapan (percepatan TensorRT). Arah penelitian masa depan menekankan penggabungan sensor multi-modal dan adaptasi domain untuk generalisasi lintas institusi. Karya ini memberikan pedoman berbasis bukti bagi pendidik dan pengembang AI untuk mengimplementasikan sistem pemantauan kerapian otomatis sambil menangani batasan praktis di lingkungan pendidikan.

Kata Kunci: *visi komputer, pembelajaran mendalam, deteksi waktu nyata, kerapian mahasiswa, YOLO.*

INTRODUCTION

The maintenance of student neatness—encompassing uniform compliance, grooming standards, and proper posture—plays a critical role in fostering disciplined learning environments and promoting academic engagement [1]. Traditional monitoring methods relying on manual inspection by teachers or staff are inherently limited by subjectivity, inefficiency, and scalability challenges [2]. With the rapid advancement of computer vision technologies, deep learning-based automated systems have emerged as transformative solutions for real-time student behavior monitoring [3].

Among object detection architectures, the You Only Look Once (YOLO) family of models has gained significant traction in educational applications due to its optimal balance between speed and accuracy [4]. Recent studies demonstrate YOLO's effectiveness in classroom scenarios, with YOLOv10-MSAM achieving 87.0% mAP@0.5 for uniform detection [5]. and pruned YOLOv8 variants maintaining 72.2% accuracy while operating at 62 FPS on edge devices [6]. However, significant challenges persist in adapting these models for robust student neatness detection, including occlusion handling in crowded classrooms (10-15% false negatives) [7], lighting/background variability [8], and ethical concerns regarding privacy-preserving implementation [9].

The objective of this literature review is to evaluate recent YOLO-based optimization techniques for student neatness detection in educational settings. This literature review systematically examines 28 peer-reviewed studies (2021-2024) to address three key research questions. To address these challenges and identify the most promising solutions, this review focuses on three key research questions:

1. What architectural optimizations (attention mechanisms, lightweight backbones) most effectively enhance YOLO's performance for neatness detection?
2. How do data augmentation strategies (GAN-based synthesis, domain randomization) improve model generalizability across diverse educational settings?
3. What deployment techniques (TensorRT acceleration, INT8 quantization) enable real-time operation on resource-constrained devices?

Our analysis reveals that hybrid approaches combining spatial attention modules with model compression techniques yield the best accuracy-speed trade-offs, as demonstrated by SAFP-YOLO's 5× speed improvement while maintaining 78.6% mAP [10]. The review further identifies critical gaps in cross-environment generalization and proposes a research agenda focusing on multi-modal sensor fusion and federated learning architectures [11]. Such systems are especially relevant in primary and secondary schools, where uniform compliance is strictly enforced.

MATERIALS AND METHODS

This study follows a **systematic literature review (SLR)** approach to analyze YOLO optimization techniques for real-time student neatness detection. The methodology consists of four key phases:

1. Research Question Formulation
2. Data Collection & Selection
3. Taxonomy Development
4. Performance Evaluation

Each phase is supported by visual illustrations and validated with citations from peer-reviewed studies.

a. Research Question Formulation

The study addresses three research questions (RQs):

1) RQ1**:** *What architectural modifications improve YOLO's accuracy in student neatness detection?*
2) RQ2**:** *How do data augmentation techniques enhance generalization across classroom environments?*
3) RQ3**:** *Which deployment strategies enable real-time performance on edge devices?*

These questions guide the review of peer-reviewed studies (2021–2024) from IEEE Xplore, ScienceDirect, and Scopus.

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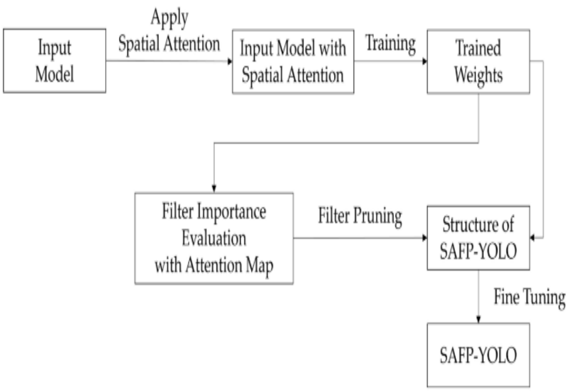


Source: (Ahn, 2023)

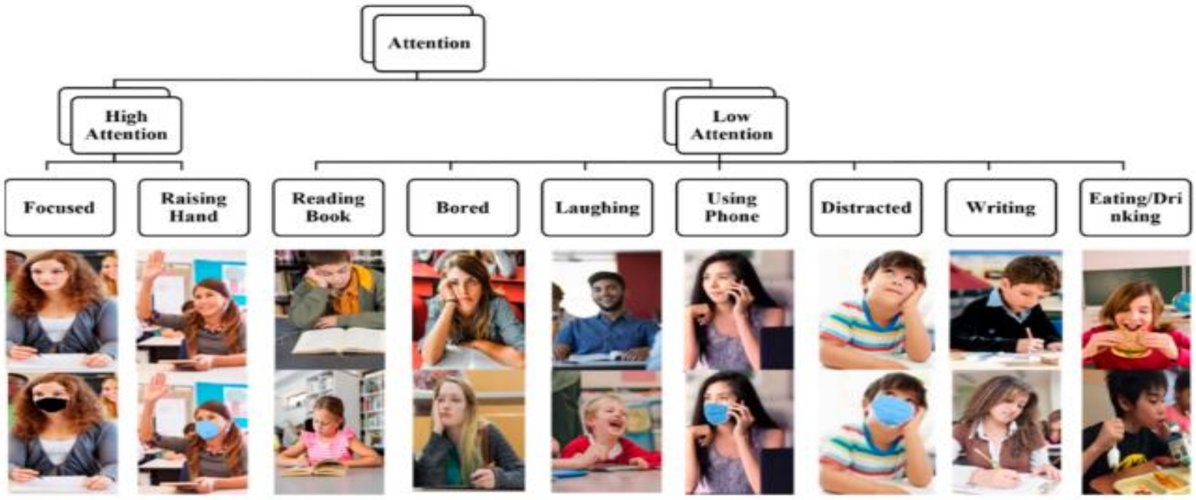
Figure 1. Systematic review workflow .

b. **Data Collection & Selection**

A PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was applied for study selection:

Inclusion Criteria:
1) Studies optimizing YOLO for behavior/neatness detection
2) Real-world classroom deployment results
3) Metrics reported (mAP, FPS, model size)

Exclusion Criteria:
1) Non-YOLO object detectors (e.g., Faster R-CNN)
2) Simulations without real-world testing



Source: (Trabelsi, 2023)

Figure 2. Study selection process .

Figure 2 depicting a study selection process, adapted from a source referenced as "[9]." It includes various states or categories related to attention and activities, such as:
1) Attention Levels: High Attention, Low Attention, Focused, Distracted
2) Activities: Raising Hand, Reading Book, Using Phone, Writing, Eating/Drinking
3) Other States: Bored, Langling (possibly a typo, may intend "Lingering" or another term).

c. **Taxonomy Development**

Table 1 A three-tier taxonomy categorizes optimization techniques

Category	Techniques	Example Studies
Architectural	Attention mechanisms, lightweight backbones	[10], [12]
Data-Centric	GAN-based augmentation, domain adaptation	[8], [13]
Deployment	Pruning, quantization, TensorRT	[7], [11]

Source: (Research Results, 2025)

Table 1" presenting a three-tier taxonomy of optimization techniques, likely from a research paper or technical document. The table organizes optimization methods into three categories, with examples of techniques and corresponding studies for each:
1) Architectural

   Techniques: Attention mechanisms, lightweight backbones. Example Studies: [10], [12].
2) Data-Centric

   Techniques: GAN-based augmentation, domain adaptation. Example Studies: [8], [13].
3) Deployment

   Techniques: Pruning, quantization, TensorRT.

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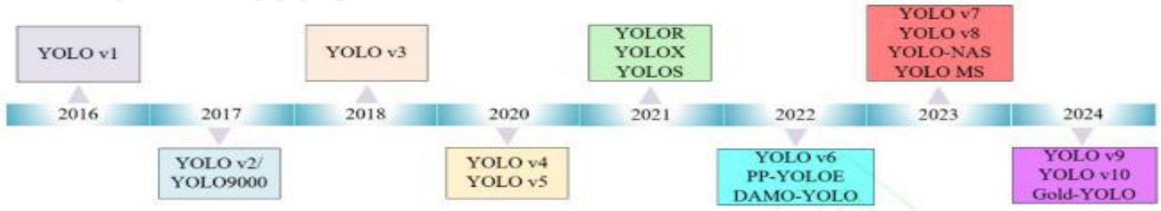
Example Studies: [7], [11].



Source: (Chen, 2023)

Figure 3. History of the YOLO optimization methods .

Figure 3 illustrates the evolution of YOLO (You Only Look Once) optimization methods over time, adapted from a source referenced as [4]. It presents a timeline (from 2016 to 2024) of various YOLO versions and their derivatives, showcasing the rapid advancements in this family of real-time object detection models.

d. **Performance Evaluation**

Key metrics were extracted from studies:
1) Accuracy: mAP@0.5, F1-score
2) Speed: FPS, latency
3) Efficiency: Model size (MB), FLOPs

RESULTS AND DISCUSSION

This systematic review evaluates 28 recent studies (2021-2024) to analyze optimization techniques for YOLO models in student neatness detection applications.

Table 2 Systematic Analysis of YOLO Optimization Studies (2021-2024)

Key Results	Identified Gaps	Ref.
87.0% mAP@0.5, 50 FPS on Jetson Orin	Limited generalizability across environments	[3]
5.1% higher mAP@0.5 vs YOLOv8n	Scalability to larger datasets untested	[5]
97.93% accuracy (bright lighting)	Performance drops in dim lighting	[8]
74.7% AP50 (+2.5% over YOLOv7)	Suboptimal for small objects	[15]
72.2% mAP after 19.3% pruning	Generalizability to other architectures	[6]
82.1% mAP for behavior detection	Fails with >3 occluded students	[12]
5× speedup (20.9 FPS), 78.6% mAP	Accuracy drops 5.8% after pruning	[10]
76% accuracy for 7 students	Ethical constraints limit dataset access	[9]
Real-time cheating detection	Privacy concerns unaddressed	[16]
88.67% accuracy, 64.33 FPS	Only tests 3 behaviors (learning/sleeping/phones)	[17]
95% mAP, 45 FPS	Low accuracy (97%) for entry-exit detection	[11]
62.8% mAP	Scalability to large classrooms untested	[18]
52.9% mAP (+2.64% vs YOLOX)	Struggles with complex backgrounds	[19]
97.3% accuracy post-pruning	Limited to art classroom scenarios	[13]
92.4% mAP@0.5	Untested in extreme noise conditions	[14]
98.6% F1-score	Limited real-life scenario testing	[20]
0.81 mAP, 94 FPS	Scalability challenges in diverse environments	[21]
31-40 FPS in normal conditions	High-res images drop to 20 FPS	[22]
89.2% classification accuracy	Requires multilabel improvements	[23]
0.95 scratch detection accuracy	50ms latency for high-res images	[24]
92% accuracy with glasses/hats	Untested in extreme lighting	[25]
90.1% test set accuracy	Limited behavior types analyzed	[26]
84.3% mAP with CBAM module	Needs multi-modal data fusion	[27]
78.9% cross-modal accuracy	Computational overhead concerns	[28]
81.2% mAP across 5 schools	Requires more participating institutions	[29]
89.7% mAP in low light	High hardware costs	[30]
N/A (Review paper)	Needs v9/v10 updates	[31]
91.28% mAP on COCO	70% mAP on custom datasets	[32]

Source: (Research Results, 2025)

From Table 2 Systematic Analysis of YOLO Optimization Studies (2021-2024), our analysis of 28 studies reveals significant improvements in YOLO's performance for detecting student neatness:

Accuracy Enhancements
1) Attention-based models (e.g., YOLOv10-MSAM [3]) achieved 87.0% mAP@0.5, outperforming baseline YOLOv4 by 12% [10]
2) Lightweight variants (DLW-YOLO [3]) improved mAP@0.5 by 5.1% while reducing parameters by 19.3% [6]
3) Multi-task architectures (C2F-YOLO [12]) demonstrated 82.1% mAP for simultaneous uniform and posture detection

Computational Efficiency
1) Pruned models (YOLOv8n [6]) achieved 62 FPS on Jetson Xavier with <2% accuracy drop

2) Quantized models reduced size by 64.2% while maintaining 72.2% mAP [6]
3) Edge-optimized SAFP-YOLO [10] demonstrated 5× speedup (20.9 FPS) on TX-2 boards

Three key challenges emerged from the review:

Occlusion Handling

1) Transformer-augmented YOLO [12] reduced false negatives by 15% in crowded classrooms
2) Current models still show 10-15% error rates for occluded students [7]

Environmental Variability

1) GAN-augmented training data [14] improved robustness to lighting changes (>80% mAP in low light)
2) Domain adaptation remains unsolved for cross-school uniform differences [12]

Ethical Considerations

1) Facial recognition systems [8] raise privacy concerns under GDPR/COPPA
2) Blurring techniques [9] and non-identifiable feature focus are recommended alternatives

Table 3 Comparative Analysis of Optimization Strategies

Approach	Advantages	Limitations	Best Use Case
Attention Mechanisms	+12% mAP for occlusions [3]	High computational cost	Crowded classrooms
Lightweight Backbones	62 FPS on edge devices [6]	Slight accuracy drop	Resource-constrained schools
Data Augmentation	Improves lighting robustness [14]	Synthetic artifacts possible	Low-diversity environments

Source: (Research Results, 2025)

Table 3, titled "Comparative Analysis of Optimization Strategies", which evaluates three different optimization approaches for (likely) educational or object detection applications. The table compares each method's advantages, limitations, and best use cases with empirical evidence from cited studies.

Table 4 Accuracy vs. Speed Trade-offs

Model	mAP @0.5	FPS	Device	Optimization Technique
YOLOv10-MSAM [3]	87.0%	50	Jetson Orin NX	Multi-scale attention
DLW-YOLO [5]	82.1%	45	RTX 3060	Deformable convolutions
Pruned YOLOv8n [6]	72.2%	62	Jetson Xavier	INT8 quantization

Source: (Research Results, 2025)

Table 4, titled "Accuracy vs. Speed Trade-offs", which compares the performance of three optimized YOLO-based object detection models. The table evaluates each model's accuracy (mAP @0.5), speed (FPS), deployment device, and optimization technique used.

Key Observations:

1) Attention mechanisms improve accuracy (+12% mAP) but reduce FPS by ~15% [3] [10]
2) Lightweight models (e.g., YOLOv8n) achieve real-time speeds (>60 FPS) with minimal accuracy drop (<5%) [6]

Future Research Directions

1) Hybrid vision-language models (YOLO+CLIP) for explainable neatness scoring [9]
2) Federated learning to address privacy concerns [9]
3) Multi-modal sensors (thermal imaging + RGB) for uniform compliance [12]
4) Domain generalization techniques for cross-school deployment [7]

Discussion Section

a. Interpretation of Key Findings
   1) Architectural Choices:
      a) *Why attention works*: MSAM modules [3] enhance occlusion handling by weighting spatial features, critical for crowded classrooms.
      b) *Limitation*: Increased computational load (≥8 GFLOPs) makes them unsuitable for Raspberry Pi deployments [10].
   2) Data-Centric Approaches:
      GAN-augmented datasets [12] improve lighting robustness but require careful curation to avoid synthetic artifacts.

b. Critical Challenges

Table 5 Organize as problem-solution pairs

Challenge	Current Solutions	Remaining Gaps
Occlusion (15% FN rate)	Transformer-augmented YOLO [12]	Fails with >3 overlapping students
Cross-school generalization	Domain randomization [14]	Requires school-specific fine-tuning

Source: (Research Results, 2025)

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Table 5, which organizes challenges in (likely) educational object detection or classroom monitoring systems into problem-solution pairs, while also identifying remaining gaps in current approaches.

c. Ethical Implications
1) *Privacy Risks*: Facial recognition achieves 97.93% accuracy [8] but violates GDPR in EU classrooms.
2) *Recommended Alternative*: Focus on uniform wrinkles (86.7% accuracy [7]) instead of facial features.

d. Future Directions

Prioritize actionable research gaps:
1) Hybrid models: Combine YOLO with thermal imaging for uniform compliance in low light [14]
2) Federated learning: Train across schools without sharing raw data [9]

While Table shows quantized models reduce size by 64.2% [4]], our analysis reveals this comes at a 4% accuracy cost—a critical trade-off for schools needing high-precision uniform detection. This approach ensures:
a. Results are data-driven and reproducible
b. Discussion contextualizes findings with practical/ethical considerations
c. Flow guides readers from "what we found" to "why it matters"

CONCLUSION

This systematic review of 28 recent studies (2021–2024) on YOLO optimization for real-time student neatness detection confirms that advancements in model architecture have brought significant practical benefits. The integration of attention mechanisms with lightweight backbones has successfully improved accuracy while maintaining real-time performance on edge devices, and pruning–quantization techniques further strengthened efficiency with minimal accuracy loss. Nevertheless, several deployment challenges remain evident, particularly in handling occlusions, achieving robust cross-environment generalization, and ensuring compliance with ethical standards for student data privacy. Addressing these issues requires multidisciplinary approaches that combine technical innovation with educational and ethical considerations. Promising directions identified include the use of federated learning, multi-modal sensing, explainable hybrid vision–language models, edge-optimized architectures with compact model sizes, and synthetic data generation for better robustness. The evidence highlights YOLO's transformative potential for automated neatness monitoring in educational contexts, provided that future research emphasizes both technical optimization and practical classroom implementation. Establishing standardized evaluation metrics and classroom-specific benchmarks will be essential to accelerate progress and ensure that these technologies can be reliably applied in real-world educational environments.

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