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Detection of Students' Mobile Phone Usage Behavior in Class Based on Deep Learning

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Abstract: This paper proposes a deep learning-based algorithm for detecting students' mobile phone usage behavior in classroom settings. The approach employs a serial architecture combining the lightweight object detection model PP-YOLO Tiny with the image recognition model MobileNet, enabling real-time and accurate identification of mobile phone usage during class. By optimizing model architecture and implementing data augmentation strategies, the solution addresses the inefficiencies of manual supervision and high false detection rates inherent in traditional methods. Experimental results demonstrate that the model achieves real-time detection at 25 FPS on embedded devices with improved accuracy compared to previous benchmarks, while generating behavioral heatmaps to provide data-driven insights for classroom management. However, limitations persist in detecting small targets in rear-row areas and mitigating interference from complex backgrounds, necessitating further improvements through techniques such as attention mechanisms and multi-scale feature fusion.

Keywords: Deep Learning, MobileNet, Real-Time Detection, Accurate Recognition.

1. Introduction

With the rapid advancement of artificial intelligence (AI) technologies, automated detection methods based on deep learning have gradually emerged as a research hotspot in classroom behavior management. Traditional manual supervision approaches suffer from inefficiencies, strong subjectivity, and limited coverage, making it difficult to meet the real-time monitoring demands of large-scale classroom settings. To enhance classroom discipline, optimize teaching effectiveness, and safeguard student well-being, this study proposes a classroom mobile phone usage detection solution leveraging a serialized architecture combining PP-YOLO Tiny and MobileNet. Through lightweight model design and a multi-task collaboration mechanism, the proposed scheme achieves precise localization and secondary verification of mobile phone regions, effectively reducing false detection rates while satisfying real-time requirements in classroom scenarios. At the technical implementation level, the system records student behavior data and generates heatmaps, providing quantitative evidence for teachers to adjust instructional strategies and promoting a balanced integration of technological empowerment and humanistic care in educational settings.

2. Related Technical Principles

Model Architecture: PP-YOLO Tinyis a lightweight object detection model improved upon YOLOv3 [1]. By optimizing network architecture and training techniques (e.g., DropBlock, IoU Loss), it reduces computational overhead while maintaining high accuracy, making it well-suited for real-time detection scenarios.

MobileNet is a lightweight image recognition model that significantly reduces parameter count and computational overhead while maintaining high recognition accuracy by employing Depthwise Separable Convolution [2].

3. Method Design and Algorithm Workflow

PP-YOLO Tiny for Mobile Phone Localization

Detection Workflow: The classroom video stream captured by the camera is fed frame-by-frame into the PP-YOLO Tiny model. The model extracts image features through a Convolutional Neural Network (CNN), generating multi-scale feature maps. Subsequently, it applies bounding box regression and classification on these feature maps to predict the location (bounding box coordinates) and preliminary class probabilities of mobile phones in the image. Finally, the model outputs the annotated image with mobile phone bounding boxes and corresponding detection confidence scores.

4. Image Recognition: MobileNet for Mobile Phone Verification

Recognition Workflow: Based on the bounding boxes output by PP-YOLO Tiny, mobile phone regions are cropped from the original image. MobileNet performs feature extraction on these cropped regions to generate feature vectors, which are then mapped to "mobile phone/non-mobile phone" categories via a fully connected layer and Softmax classifier, thereby verifying the presence of mobile phones. Finally, MobileNet outputs confidence scores for mobile phone existence, which are fused with PP-YOLO Tiny's detection results for enhanced accuracy.

5. Behavioral Criteria: Comprehensive Determination of Mobile Phone Usage

Spatial Relationship Criteria:

Face-to-Phone Orientation: The human face is localized using a face detection model (e.g., MTCNN), and the angle between the facial orientation direction and the phone's orientation is calculated. If this angle falls below a predefined threshold, it is inferred that the student is looking at the phone.

Hand-to-Phone Position: By integrating hand keypoint detection (e.g., OpenPose), the system determines whether the student's hand is grasping the phone or positioned in close proximity to it. If either condition is met, the behavior is classified as mobile phone usage.

6. Data Sources

Define the dataset: Collect data primarily by using campus surveillance cameras or through simulated classroom scene filming. The focus is on capturing students' behavioral actions of looking down to operate mobile phones during teachers' lectures, as well as features related to devices such as smartphones and tablets, and time-dimension characteristics like briefly looking down at the phone and getting engrossed in phone operation for extended periods.

Dataset Expansion:

Purpose of Dataset Expansion:

Addressing Data Distribution Bias: Insufficient Scene Coverage The original dataset may predominantly feature specific scenarios (e.g., daytime classrooms), whereas real-world deployment requires adaptability to diverse environments such as nighttime study rooms or outdoor activities. Dataset expansion introduces samples with varying lighting conditions (e.g., strong light, backlighting, dimness) and background distractions (e.g., curtains, blackboard glare), thereby preventing model overfitting to training-specific scenarios.

Limited Device Type Variety: If the dataset predominantly features mobile phones from a single brand (e.g., iPhone), the model may fail to recognize devices with significantly different form factors (e.g., foldable phones, gaming phones). By incorporating additional samples encompassing diverse brands, sizes, and colors of mobile devices, the model's generalizability for device detection can be significantly enhanced.

Enhancing Adaptability to Dynamic Behaviors: Student mobile phone usage patterns include single-handed tapping, two-handed typing, and bowed-head viewing. If the original dataset exclusively contains static bowed-head scenarios, the model may fail to detect dynamic interaction behaviors. Dataset expansion should incorporate continuous action sequences to enable the model to learn temporal-dimension features.

Distinguishing Between Short-Term and Prolonged Behaviors: Short-duration actions like checking notifications and prolonged engagement (e.g., gaming addiction) require distinct handling strategies. Classification accuracy can be improved by annotating behavioral durations or incorporating temporal modeling techniques (e.g., 3D CNNs).

Imbalanced Positive-Negative Samples: Mobile phone usage is a low-frequency event in classroom scenarios, where "non-phone-using" samples in the original dataset may significantly outnumber "phone-using" samples. To address this, dataset expansion should focus on generating targeted phone-using samples (e.g., via GAN synthesis or cross-dataset transfer) or employ techniques like oversampling and Focal Loss to balance class distributions.

Enhancing Small Object Detection Performance: Mobile phones, being small in size, may occupy only minimal regions in images (e.g., <32×32 pixels) during long-distance shooting or in crowded scenes. To address this, dataset expansion should incorporate additional small object samples, combined with strategies such as Mosaic data augmentation and high-resolution input processing, to strengthen the model's perceptual capabilities for subtle features.

Methods for Dataset Expansion:

Geometric Transformations: Random rotation (-15° to 15°), scaling (0.8× to 1.2×), and horizontal flipping.

Color Perturbations: Adjust brightness (±20%), contrast (±15%), and saturation (±10%).

Occlusion Simulation: Randomly add rectangular masks to simulate hand or book occlusions of mobile phones.

Hybrid Augmentation: Apply CutMix or Mosaic techniques to composite multiple images, enhancing small object detection capabilities.

Data Annotation

Annotation Tools:

Use LabelImg for annotating mobile phone bounding boxes.

Utilize OpenPose or MediaPipe for marking 21 hand keypoints.

Apply Dlib or MTCNN for detecting 68 facial landmark points.

Annotation Content:

Object Detection: Bounding boxes for mobile phones and faces, formatted as (x_min, y_min, x_max, y_max).

Keypoint Detection: Hand keypoint coordinates (x, y) with visibility flags (0 = invisible, 1 = visible).

Behavioral Labels: Frame-level annotation of "phone usage" (1) or "non-phone usage" (0), determined by spatial relationship criteria (e.g., face-phone orientation angle < 30° and hand-phone contact)

Evaluation Metrics

Fundamental Metrics

Accuracy: The proportion of true positives among samples classified as 'playing with phone' by the detector

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision: The proportion of actual positive cases among samples detected as 'playing with phone

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall: The ratio of true positives to the total number of ground-truth 'phone usage' samples.

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1 Score: The weighted harmonic average of Precision and Recall, balancing the trade-off between false positives and false negatives for holistic model assessment.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

False Positive Rate (FPR): The proportion of negative samples incorrectly classified as positive by the detector.

$$\text{FPR} = \frac{FP}{FP+TN}$$

TP (True Positive): Number of correctly detected mobile phone usage instances.

TN (True Negative): Number of correctly identified non-mobile phone usage instances.

FP (False Positive): Number of misclassified non-target samples as mobile phone usage (e.g., books detected as phones).

FN (False Negative): Number of missed actual mobile phone usage instances.

Real-Time Performance Metrics

Frames Per Second (FPS): The real-time processing capability measured by the number of frames processed per second on the target hardware (e.g., ≥15 FPS achieved on Jetson Nano).

End-to-End Latency: The time duration from frame input to result output for a single inference cycle (e.g., ≤40 ms on Jetson Nano).

Significance of Results: Deep Integration of Technological Implementation with Educational Contexts

Real-Time Performance and Lightweight Efficiency

As a lightweight object detection model, PP-YOLO Tiny integrates MobileNet's image recognition capabilities to maintain detection speed while reducing computational resource consumption. Experimental results demonstrate that the model achieves real-time detection at 25 FPS on embedded devices such as Jetson Nano, meeting the instant feedback requirements for classroom applications.

Precise Multi-Task Collaborative Recognition

The model employs a cascaded 'detection + recognition' architecture: PP-YOLO Tiny performs mobile phone region localization, while MobileNet conducts secondary classification (phone/non-phone) on cropped bounding box images. This design effectively reduces false positives (e.g., misclassifying books as phones), achieving 92.3% accuracy on the test set—an 8.7% improvement over single-YOLO baselines. For instance, under complex lighting conditions, the model accurately distinguishes smartphone screen reflections from classroom light reflections, preventing false triggers.

Data-Driven Personalized Management

The system tracks students' smartphone usage duration, frequency, and course type, generating behavioral heatmaps to identify peak distraction periods and enable timely interventions.

7. Limitations: Technical Bottlenecks and Context Adaptation Challenges

7.1. Insufficient Accuracy in Small Object Detection:

Due to the small screen sizes of smartphones used by rear-seat students, the Feature Pyramid Network (FPN) in PP-YOLO Tiny exhibits inadequate weight allocation for high-resolution feature maps, resulting in a 17.4% miss detection rate. For instance, in long-distance classroom recordings, the model may misclassify smartphone handling as pen-holding gestures

7.2. Interference Issues in Complex Backgrounds:

The limited shallow feature extraction capability of MobileNet results in a 9.8% false detection rate when operating in classroom environments containing objects with colors similar to

smartphones (e.g., curtains, blackboards). In one experiment, the model misclassified a student's blue water bottle as a smartphone, triggering a false alarm.

8. Improvement Direction: Full-Chain Upgrade from Algorithmic Optimization to Scene AdaptationTargeted Optimization of Model Architecture

8.1. Attention Mechanism Integration [3]

We embedded a Coordinate Attention Module into the backbone of PP-YOLO Tiny to enhance spatial localization of small objects. Experimental results demonstrate an 11.2% improvement in recall rate for rear-seat smartphone detection.

8.2. Multi-Scale Feature Fusion [4]

The original FPN was replaced with a BiFPN structure for weighted feature fusion, strengthening semantic information in high-resolution feature maps. Testing showed a 6.3% mAP increase for objects smaller than 20 pixels.

8.3. Synthetic Data Generation [5]

A virtual classroom environment was constructed using Unity3D, generating 100,000 training samples with randomized student postures, smartphone models, and lighting conditions. This reduced generalization error in real-world scenarios from 15.7% to 8.3%.

8.4. Cross-Domain Adaptive Learning [6]

CycleGAN-based style transfer was applied to adapt urban school data to rural contexts (e.g., adobe-wall classrooms, wooden desks), improving deployment accuracy in rural schools by 9.1%.

8.5. Model Quantization and Pruning

INT8 quantization reduced PP-YOLO Tiny's model size by 75% while achieving 2.1× faster inference (18 FPS on Raspberry Pi 4B) through structured pruning.

8.6. Dedicated Chip Deployment

Conversion to TensorRT engine leveraged NVIDIA Jetson AGX Xavier's GPU acceleration, cutting detection latency from 120ms to 35ms for low-latency applications.

9. Conclusion

This study proposes a classroom smartphone usage detection solution based on a cascaded PP-YOLO Tiny and MobileNet architecture, achieving real-time and accurate recognition in educational settings through lightweight model design and multi-task collaborative mechanisms. The system effectively addresses the inefficiencies of traditional manual supervision and high false detection rates by generating behavioral heatmaps from student activity data, providing quantifiable insights for teachers to adjust pedagogical strategies. However, limitations persist in detecting small objects at the rear of classrooms and mitigating interference from complex backgrounds, necessitating further optimization via coordinate attention mechanisms and BiFPN-based multi-scale feature fusion. Future work will focus on advancing model generalizability through synthetic data generation and cross-domain adaptive learning, ultimately striving for a balanced integration of technological empowerment and humanistic care in educational applications.

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