

YOLOV8 DETECTION FOR STUDENT DRESS CODE COMPLIANCE USING COMPUTER VISION

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Abstract: The implementation of dress code regulations in university environments is generally still carried out conventionally, requiring significant time and effort and potentially leading to subjective assessments. This study develops an automatic student dress code compliance detection system using computer vision based on the YOLOv8 model. The dataset consists of 1,800 annotated images divided into eight clothing categories, split into 78% training (1,404 images), 14% validation (254 images), and 8% testing (143 images). All images underwent preprocessing and data augmentation before training the YOLOv8 model with an input size of 640×640 pixels for 50 epochs. During testing, the YOLOv8 model achieved an overall performance of Precision 0.844, Recall 0.773, F1-Score 0.802, and mAP@0.5 0.841, and was able to detect clothing objects with good accuracy and stable performance under various image conditions. The system was integrated with a Flask-based backend and a web-based frontend to enable real time detection and compliance classification, with a response time of less than 2 seconds, supporting automatic and consistent identification of student dress code compliance as “Compliant” or “Violation.”

Keywords: compliance detection; computer vision; dress code regulations; real time detection; YOLOv8.

Abstrak: Penerapan aturan berpakaian di lingkungan kampus umumnya masih dilakukan secara konvensional sehingga membutuhkan waktu dan tenaga yang relatif besar serta berpotensi menimbulkan subjektivitas penilaian. Penelitian ini bertujuan mengembangkan sistem pendekripsi kepatuhan berpakaian mahasiswa secara otomatis berbasis visi komputer menggunakan model YOLOv8. Dataset yang digunakan terdiri dari 1.800 citra beranotasi yang terbagi ke dalam 8 kategori pakaian, dengan pembagian data sebesar 78% data latih (1.404 citra), 14% data validasi (254 citra) dan 8% data uji (143 citra). Seluruh citra diproses melalui tahapan pre-processing dan data augmentation, kemudian digunakan untuk melatih model YOLOv8 dengan ukuran input 640×640 piksel selama 50 epoch. Pada tahap pengujian, model mencapai performa keseluruhan dengan Precision 0.844, Recall 0.773, F1-Score 0.802, dan mAP@0.5 0.841, serta mampu mendekripsi objek pakaian dengan akurasi baik dan performa stabil pada berbagai kondisi citra. Sistem kemudian diintegrasikan dengan backend berbasis Flask dan frontend web untuk mendukung proses deteksi waktu nyata dan klasifikasi kepatuhan, dengan waktu respons sistem kurang dari 2 detik, sehingga mampu mengidentifikasi status kepatuhan berpakaian mahasiswa ke dalam kategori “Aman” dan “Melanggar Aturan” secara otomatis dan konsisten.

Kata kunci: aturan berpakaian; deteksi waktu nyata; pendekripsi kepatuhan; visi komputer; YOLOv8.

INTRODUCTION

Higher education institutions are formal educational entities that play a strategic role in shaping human resources with strong character and ethical values. As institutions responsible for developing superior generations, universities have a moral obligation to instill and enforce ethical principles among all members to foster a healthy, conducive, and integrity-driven academic environment [1]. To support this objective, universities implement regulations as guidelines to manage student behavior, including attitudes, conduct, and appearance [2].

As part of academic regulations, universities establish dress codes that students are required to follow. Proper dressing etiquette represents a process through which individuals present harmony and neatness in their attire according to the occasion [3]. Within the academic context, students' dressing ethics reflect their morality and integrity in cultivating a healthy and respectable academic culture [4].

Despite the established dress codes, noncompliance among students remains prevalent. Several studies indicate that students often wear clothing unsuitable for academic settings, favoring casual styles, both among female and male students, which may compromise a conducive academic atmosphere [5]. This situation highlights a gap between established rules and student behavior, influenced by ineffective enforcement, weak supervision, and limited lecturer involvement in guiding and educating students about dress code compliance [6].

In enforcing dress codes, supervision is generally carried out manually by lecturers, campus security, or staff. Conventional monitoring systems present several limitations, including inaccurate

data recording, potential manipulation, and inability to track supervisory activities in real-time [7]. In large student populations, dress code violations often go unnoticed, requiring a technology-driven enforcement approach.

To address the limitations of conventional monitoring, computer vision technology offers a promising solution for supervising student dress code compliance. Computer vision, a branch of artificial intelligence, enables systems to recognize, classify, and analyze visual information from images or videos using edge computing, cloud computing, and deep learning models [8]. Leveraging these capabilities allows for automated, objective, and real-time monitoring without complete dependence on manual oversight.

Previous studies have shown that deep learning-based object detection models, particularly YOLO, achieve strong performance in various computer vision tasks. A study using YOLOv8 for inorganic waste detection reported an mAP@0.5 of 87.1% with precision and recall of 86.2% and 79.1%, respectively [9]. Another study applied YOLOv7 for vehicle detection and achieved a precision of 93.22%, recall of 90.64%, and mAP@0.5 of 94.27% [10]. However, the application of YOLO-based models for monitoring student dress code compliance in higher education remains limited.

Based on this research gap, this study aims to implement YOLOv8 to detect student dress code compliance using computer vision. The study also evaluates model performance using precision, recall, and mean Average Precision (mAP) metrics. The results are expected to provide a more objective and efficient solution for monitoring student adherence to dress code regulations in higher education settings.

METHOD

The research methodology employed in this study comprises six main stages, as illustrated in Image 1.

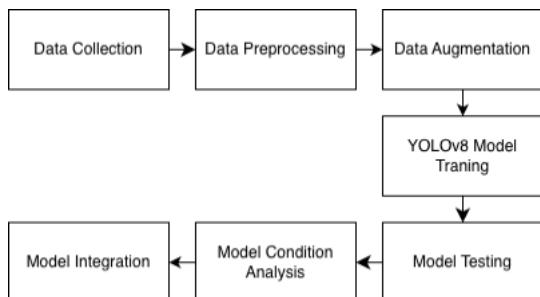


Image 1. Research Methodology Diagram

Image 1 presents the workflow of the research, which includes six key steps: data collection, data preprocessing, data augmentation, YOLOv8 model training, model testing, analysis of confidence levels under varying lighting conditions and object distances, and integration into the backend and frontend systems.

Data Collection

The dataset used in this study was obtained from the Roboflow platform and consists of 1,800 images divided into eight clothing categories: T-shirt, dress, jacket, pants, shirt, shorts, skirt, and sweater. These categories were chosen to represent common clothing worn by students on campus, making the dataset relevant for analyzing adherence to dress code regulations. The dataset was split into training (1,404 images, 78%), validation (254 images, 14%), and test (143 images, 8%) sets.

Data Preprocessing

Data preprocessing was conducted to prepare the dataset for object detection. Image labeling was performed au-

tomatically using the Roboflow platform, where each clothing object in the image was annotated with a bounding box corresponding to its class.



Image 2. Roboflow Auto Labeling

Image 2 illustrates the auto-labeling process in Roboflow, where each clothing item is automatically enclosed within a bounding box and assigned a corresponding class label. Once the labeling process is completed and the dataset is exported, the images are organized in a folder, while the annotations are stored as text files in a separate labels folder. Each text file contains the bounding box coordinates and the class information for the corresponding image.

Data Augmentation

To improve the YOLOv8 model's robustness, data augmentation was applied to the training set, including horizontal flipping, random rotation ($\pm 15^\circ$), and brightness and contrast adjustments. Augmented images retained their bounding boxes and class labels in YOLO format. This expanded training set, while leaving validation and test sets unchanged, introduced variations in poses, lighting, and minor geometric changes, helping the model better generalize to different image conditions.

Model Training

This research uses the YOLOv8 model to detect and classify student

clothing in images. The model was trained using Google Colab with a Tesla T4 GPU. A total of 1,404 images from augmentation dataset were used for training. The training process was carried out for 50 epochs so that the model could learn clothing patterns properly without overfitting. A batch size of 16 was chosen to ensure efficient training on the available hardware. The input image size was set to 640×640 pixels to maintain sufficient image detail for clothing detection. After training, the model was evaluated using 254 validation images to measure its performance.

Model Testing

After validation, the model was evaluated using a test set consisting of 143 images. The purpose of this testing phase was to assess the model's ability to recognize clothing items it had not encountered during training.

Model performance was evaluated using a confusion matrix to analyze the distribution of correct and incorrect predictions across classes. Precision and recall metrics were used to measure prediction quality, where precision indicates the accuracy of detections, and recall measures the model's ability to detect all relevant objects:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

Additionally, the F1-score was calculated as the harmonic mean of precision and recall, providing an overall assessment of the model's performance. A high F1-score indicates that the model can produce accurate predictions while capturing most of the existing objects:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

The evaluate detection performance for each class, the mean Average Precision (mAP) metric was used. mAP computes the average precision at various Intersection over Union (IoU) thresholds per class, reflecting the model's ability to consistently detect all object categories:

$$\text{mAP}@0.5 = \frac{1}{N} \sum_{i=1}^N \text{AP}_i \quad (4)$$

Description:

N is the number of classes

AP_i represents the average precision for the i-th class with IoU ≥ 0.5 .

The combination of these four metrics ensures that the YOLOv8 model demonstrates stable and reliable performance in detecting various types of student clothing [11].

Model Condition Analysis

Model condition analysis was performed to evaluate the robustness of the YOLOv8 model under varying lighting and distance conditions. Two test images representing shirt–short and shirt–pants combinations were selected based on campus dress code regulations. Each image was automatically modified to produce four variations, namely bright lighting, dim lighting, close distance, and far distance, resulting in a total of eight test images. This evaluation aims to assess the model's consistency and reliability in detecting student clothing under different visual conditions that commonly occur in real-world environments.

Model Integration

The trained YOLOv8 model was integrated with a Flask-based backend to enable web deployment. The backend receives image or video input, performs real-time detection using OpenCV, and returns class labels, bounding boxes, and

confidence scores to the frontend. Clothing compliance logic categorizes detected items as “violating rules” if shorts, skirts, or missing primary clothing are found, and “compliant” if T-shirts, shirts, pants, jackets, dresses, or sweaters are fully detected. Detection results are stored for reporting, allowing the system to automatically assess and display student dress compliance.

RESULT AND DISCUSSION

Model Validation Metrics

The performance evaluation of the YOLOv8 model is presented in Table 1, which shows the precision, recall, F1-score, and mAP@0.5 for each clothing class using 254 validation images.

Table 1. Model Validation Metrics

Label	Metrics			
	Precision	Recall	F1	mAP @0.5
T-Shirt	0.698	0.724	0.710	0.805
Dress	0.739	0.687	0.712	0.812
Jacket	0.677	0.818	0.741	0.805
Pants	0.833	0.883	0.857	0.912
Shirt	0.534	0.506	0.519	0.602
Short	0.819	1	0.900	0.962
Skirt	0.853	0.712	0.777	0.842
Sweater	0.671	0.664	0.667	0.694

Based on Table 1, the YOLOv8 model achieved the highest performance on the Shorts and Pants classes, with both precision and recall indicating most objects were correctly detected. The Jacket class showed high recall (0.818) but lower precision (0.677), suggesting

occasional misclassification of non-jacket items, while the Skirt class exhibited high precision (0.853) but lower recall (0.712), indicating that several skirt instances were missed despite accurate predictions. Other classes, including T-shirt, Dress, and Sweater, showed moderate performance, and the Shirt class had the lowest detection rates due to visual similarity with T-shirts. Differences between precision and recall were primarily influenced by similarities between clothing items and variations in lighting and pose.

Model Testing Results

The model testing was conducted on a test set of 143 images, and the results are presented in a confusion matrix in Image 3.

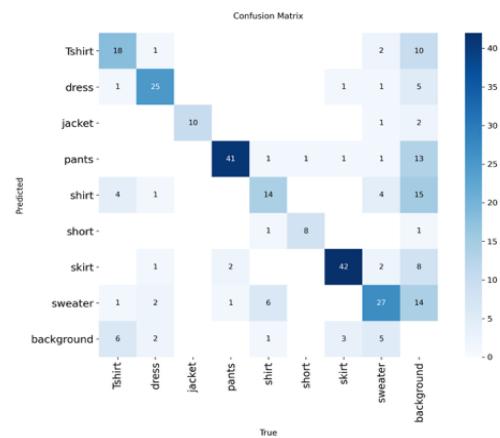


Image 3. Confusion Matrix Test Set

Based on the confusion matrix, Pants and Skirt performed best, with 41 and 42 correct predictions, while Dress (25) and T-Shirt (18) showed moderate performance. Shirt had the lowest accuracy, with only 14 correct predictions and frequent misclassifications into T-Shirt or background. Background was also often misdetected as clothing, indicating that the model struggles to distinguish visually similar items and is affected by

variations in lighting.

Table 2. Model Testing Results

Label	Metrics			
	Precision	Recall	F1	mAP @0.5
T-Shirt	0.868	0.633	0.732	0.749
Dress	0.857	0.748	0.799	0.839
Jacket	0.908	0.9	0.904	0.978
Pants	0.794	0.909	0.848	0.923
Shirt	0.7	0.783	0.739	0.706
Short	0.962	0.889	0.924	0.903
Skirt	0.837	0.765	0.799	0.853
Sweater	0.828	0.56	0.667	0.774

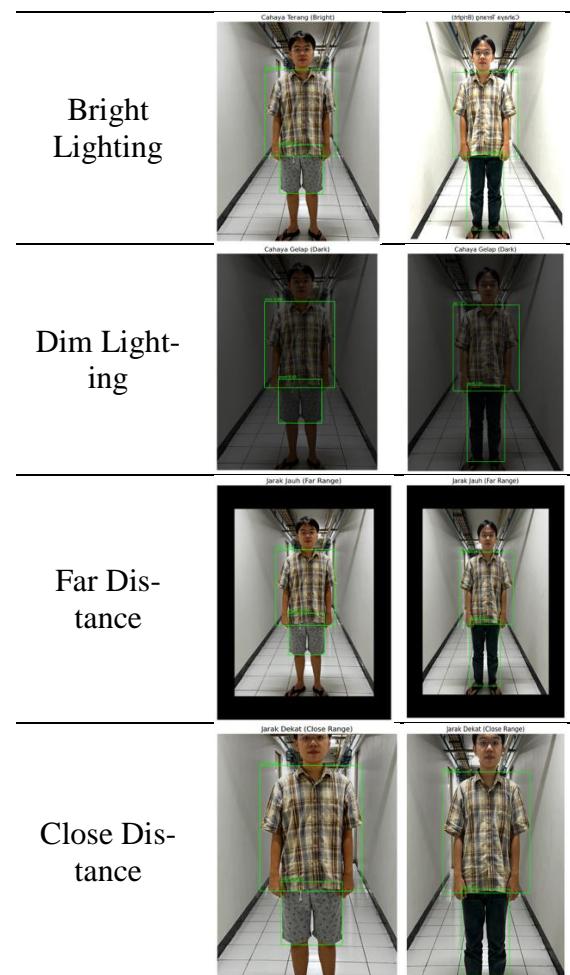
Based on table model testing result, the YOLOv8 model generally performed well on the test set. Shorts and Jacket achieved the highest precision and recall, meaning most instances were correctly detected, while classes like T-shirt, Sweater, and Skirt showed lower recall, indicating some objects were missed. Compared to the validation results, certain classes exhibited different trends in precision and recall, likely due to variations in pose, lighting, and class distribution in the unseen test data. These findings show that although the model is effective overall, its detection accuracy can vary depending on the specific conditions of new data.

Condition Analysis

In the table 3 presents the YOLOv8 model performance under different lighting and distance conditions for shirt–short and shirt–pants image scenarios, showing how visual variations affect detection confidence.

Table 3. Analysis Condition Results

Conditions	Image 1	Image 2
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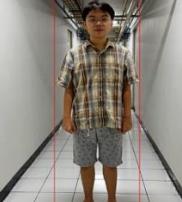
Based on Table 3, for the shirt–short combination, confidence under dim lighting was 0.84 (shirt) and 0.50 (short), while bright lighting kept the shirt at 0.84 but lowered short to 0.31. Confidence increased with proximity, reaching 0.93 (shirt) and 0.80 (short) at close distance. For shirt–pants, dim lighting gave 0.72 (shirt) and 0.90 (pants), rising to 0.90 and 0.92 under bright lighting, dropping to 0.87 and 0.63 at far distance, and returning to 0.92 and 0.90 at close distance. Overall, the model performs best at close distance and bright lighting, detecting pants more reliably than shorts.

Clothing Compliance Evaluation

Clothing compliance was evaluated

based on the YOLOv8 model's detection of clothing classes. Detected items were then classified as Compliant or Violating Rules, and a summary of the results is presented in Table 4.

Table 4. Clothing Compliance Evaluation

Image	Description
	Compliance
	Violation

According to Table 4, the system automatically classified clothing as Compliant or Violating Rules based on YOLOv8 detection, with shorts, skirts, or missing primary clothing considered violations. The Flask-based backend processed image or video input in real-time using OpenCV, and the results were displayed on the web interface.

Model Integration

Image 4 shows the web interface where the system integrates the YOLOv8 model to detect clothing and evaluate compliance in real time.

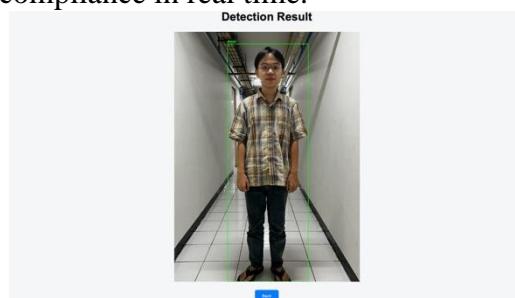


Image 4. Web Interface

Image 4 presents the web interface of clothing compliance detection

result. The system displays bounding boxes around detected objects along with compliance status labels, either Compliant or Violating Rules.

Image 5 shows the system interface used for integrating the detection model with the web-based application. This interface allows users to provide input data that will be processed by the system.

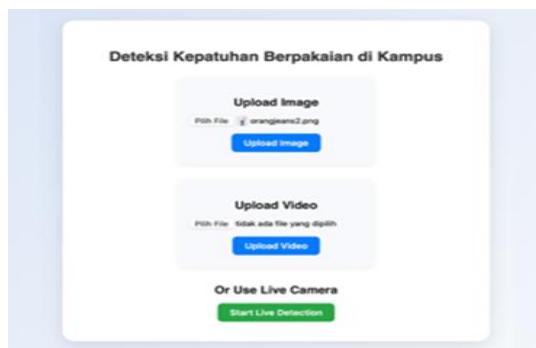


Image 5. Upload File Frontend

CONCLUSION

This research presents the development of an automatic student dress code compliance detection system using the YOLOv8 model. The proposed system is capable of detecting and classifying various types of student clothing in images with satisfactory performance, enabling objective and efficient monitoring of dress code compliance in campus environments. The experimental results demonstrate that the model performs consistently under different lighting and distance conditions, indicating its potential applicability in real-world scenarios. However, several limitations remain. The model's performance may decrease when clothing items have similar visual characteristics that reduce visual clarity. Future work will focus on expanding clothing categories, improving robustness under extreme lighting conditions, and increas-

ing dataset diversity to further enhance detection accuracy and generalization performance.

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