Development of a Multi-Class Dress Code Detection System Utilizing RoboFlow Object Detection Model v3

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***Abstract*—Dress code violations in educational institutions present ongoing challenges for administrators striving to maintain a balance between enforcing standards and fostering a sense of individuality among students. This study seeks to address these challenges by developing an innovative multi-class dress code detection system utilizing the RoboFlow Object Detection Model v3. The motivation for this study stems from the need for a systematic and efficient method to manage dress code policies while promoting inclusivity and self-expression within school environments. The proposed system categorizes dress codes into four classes: school uniforms, organizational shirts, civilian attire, and formal wear. The research methodology encompasses meticulous data collection from a dataset of 10,000 images, preprocessing steps to enhance image quality, data augmentation to improve model robustness, and model training using the advanced COCOn checkpoint for high-performance object detection. Key preprocessing techniques include resizing, contrast adjustment, and cropping, while augmentation processes introduce variations to improve adaptability. The evaluation metrics reveal exceptional performance, with a Mean Average Precision (mAP) of 99.5%, precision of 99.8%, and recall of 100.0%. This system demonstrates the ability to accurately and efficiently identify and classify dress codes, offering significant improvements over existing approaches. Comparative analysis highlights its superiority in terms of precision and reliability, making it a practical solution for schools aiming to streamline dress code enforcement. Future work will explore the inclusion of larger datasets and integration with emerging object detection technologies to further refine accuracy and expand applicability. This study sets a benchmark for utilizing AI in educational policy enforcement, contributing to a more structured and inclusive campus environment.**

Keywords— Dress Code Detection, RoboFlow Object Detection, Multi-Class Classification, Image Recognition, School Dress Code, Data Augmentation, Model Training, Educational Settings, Machine Learning, Computer Vision.

I. Introduction

Dress code violations remain a recurring issue for educational institutions, disrupting campus discipline and placing significant demands on administrative resources [1]. Manual enforcement processes are prone to inconsistencies and subjectivity, making them inadequate for achieving fairness and reliability in dress code compliance [2]. Creating a structured and automated approach to enforcement can ensure adherence to policies while promoting inclusivity and individuality among students, essential elements of a positive school culture [3].

The field of object detection and classification has seen rapid advancements, enabling the development of robust systems for automated policy enforcement. Techniques such as the YOLO framework have been widely adopted for their real-time detection capabilities. YOLO's architecture excels in applications requiring speed and accuracy, including industrial monitoring and compliance detection, though its adaptability to diverse datasets remains limited [8]. MobileNetV2, a lightweight framework designed for constrained computational environments, balances efficiency and accuracy but struggles to achieve high recall rates, a critical factor in contexts demanding comprehensive compliance monitoring [9].

RoboFlow Object Detection Model v3 introduces a versatile and scalable solution for multi-class classification tasks. Equipped with pre-trained checkpoints like COCOn, the model leverages advanced data augmentation and preprocessing techniques to enhance detection precision and adaptability across varied settings [5], [6]. These characteristics make RoboFlow particularly suitable for addressing challenges in dress code compliance, a domain where traditional methods fall short in scalability and objectivity [7].

The study aims to develop a multi-class dress code detection system capable of categorizing attire into four classes: school uniforms, organizational shirts, civilian attire, and formal wear [4]. Grounded in advancements in computer vision and machine learning, this research addresses gaps in existing methods, situating the proposed system as a critical contribution to the growing field of AI-driven educational management solutions.

II. Methodology

This study employs a systematic approach to develop a multi-class dress code detection system using the latest Roboflow 3.0 Object Detection (Fast) model with a COCOn checkpoint. The methodology is structured into several key phases: data collection, preprocessing, data augmentation, model training, and evaluation. Each phase is meticulously designed to ensure the accuracy and efficiency of the model in identifying and classifying various dress codes. This comprehensive approach leverages advanced image recognition and classification techniques to address the issue of dress code violations in educational settings.

A. Data Collection

Data collection involved randomly taking pictures of different students, resulting in a dataset comprising 3,083 images of organizational shirts, 2,701 images of civilian

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attire, 2,696 images of uniforms, and 1,520 images of formal wear. The data were split into training (70%), testing (20%), and validation (10%) sets for each class.

B. Data Preprocessing

For preprocessing, the proponents applied several steps to enhance the image quality and prepare the data for model training. These steps included auto-orienting the images, applying a static crop to capture 25-75% of the horizontal and vertical regions, resizing the images to 640x640 pixels, and using adaptive equalization for auto-adjusting contrast.

C. Data Augmentation

Data augmentation was also employed to increase the robustness of the model. Each training example produced three augmented outputs with the following modifications: a crop with 0% minimum zoom and 20% maximum zoom, saturation adjustments between -25% and +25%, brightness changes between -15% and +15%, exposure adjustments between -10% and +10%, blur up to 2.5 pixels, and noise affecting up to 0.1% of the pixels.

D. Classification Model

The model used for this study was the Roboflow 3.0 Object Detection (Fast) with a COCOn checkpoint. This is the latest free model available on the Roboflow platform, offering advanced object detection and classification capabilities. The COCOn checkpoint provides pre-trained weights based on a comprehensive dataset, enhancing the model's ability to quickly adapt to specific classification tasks.

III. Data and Results

This chapter includes a variety of graphs, numerical data, and visual aids to help illustrate the key points. One of the highlights is Figure 1, which shows examples of image outputs from our model, along with how confident the model is in each of its classifications. Essentially, the higher the confidence level, the more accurate we can expect the model's classification to be.

Fig. 1. Sample Image Output processed by the Model

Figure 2 illustrates the Mean Average Precision (mAP) over 100 epochs. Initially, there are fluctuations as the model adjusts and learns the features of the dataset. However, the mAP quickly approaches 1.0 within the first few epochs and stabilizes, indicating that the model rapidly learns and maintains high precision and recall throughout the training process. This rapid stabilization showcases the efficiency of the model in learning to detect and classify dress codes accurately.

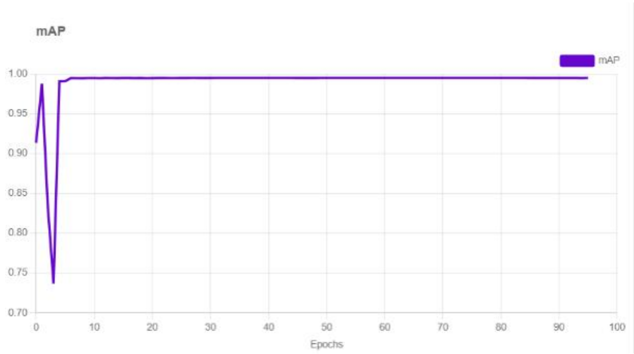

Fig. 2. Mean Average Precision (mAP) per Epoch

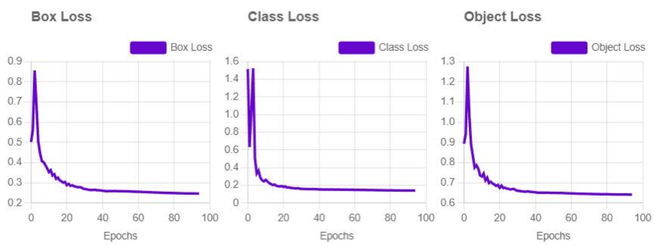

Fig. 3. Losses per Epoch

Figure 3 presents the loss metrics for box loss, class loss, and object loss over 100 epochs. Box loss, which measures the error in predicting the bounding boxes around detected objects, shows a sharp decline in the initial epochs and then gradually reduces and stabilizes. This pattern indicates that the model quickly learns to accurately predict the bounding boxes for the dress codes. Class loss, which measures the error in predicting the class labels of the detected objects, also decreases sharply initially and then stabilizes, showing the model's increasing accuracy in classifying the dress codes correctly. Similarly, object loss, which measures the error in detecting the presence of objects, shows a rapid decrease and stabilization, indicating the model's proficiency in identifying whether an object (dress code) is present in an image.

Fig. 4. Model Metrics

The performance metrics for the proposed model demonstrate exceptional accuracy and reliability in multi-class dress code classification. The model achieved a Mean Average Precision (mAP) of 99.5%, precision of 99.8%, and recall of 100.0%, reflecting its robust ability to identify and classify dress codes with minimal errors. The near-perfect precision value indicates the model's effectiveness in avoiding false positives, ensuring that misclassifications are rare. Similarly, the perfect recall score highlights the model's capability to detect all instances of dress code violations, eliminating false negatives and ensuring comprehensive compliance monitoring.

These metrics collectively suggest that the system is highly effective in addressing the challenges of dress code detection within educational settings. The high mAP score further underscores the model's consistency across all categories, affirming its adaptability and robustness when applied to diverse and complex datasets. Such performance establishes the proposed model as a reliable and scalable solution for automated dress code enforcement, capable of meeting the stringent demands of policy adherence in institutional environments..

TABLE I. COMPARATIVE PERFORMANCE ANALYSIS OF DRESS CODE DETECTION MODELS

Metrics	RoboFlow Object Detection Model v3 (This Study)	MobileNet V2 [9]	YOLO - CPDC [8] framework
F1 Score	99.5	0.68	0.99
Precision	99.8	0.81	0.99
Recall	100	0.59	0.985

Table 1 presents a comparative analysis of the proposed dress code detection system based on the RoboFlow Object Detection Model v3 against two widely recognized models, YOLO-CPDC and MobileNetV2, in terms of key performance metrics: F1 Score, precision, and recall. This comparative assessment highlights the strengths and limitations of each model within the context of dress code compliance detection.

The RoboFlow Object Detection Model v3 outperforms the other models in all metrics, with an F1 Score of 99.5, precision of 99.8, and recall of 100.0. These results underscore the model's exceptional ability to accurately classify various dress codes while minimizing false positives and false negatives. The high precision and recall values indicate the model’s reliability in both identifying correct classifications and ensuring no significant errors are overlooked.

In contrast, the YOLO-CPDC framework demonstrates competitive performance with an F1 Score of 0.99, precision of 0.99, and recall of 0.985. Although its metrics are close to RoboFlow's, YOLO-CPDC exhibits minor limitations in recall, which may lead to occasional misses in dress code violations, especially in more complex datasets. Its robustness and balance make it a strong contender but less optimal for tasks demanding near-perfect compliance detection.

MobileNetV2 achieves the lowest performance across all metrics, with an F1 Score of 0.68, precision of 0.81, and recall of 0.59. While its lightweight architecture provides efficiency in resource-constrained environments, its low recall suggests significant difficulty in capturing all instances of dress code violations, rendering it less suitable for stringent compliance tasks.

This comparative analysis highlights the advantages of the RoboFlow-based system, including its advanced object detection capabilities, adaptability, and precision. However, the reliance on pre-trained checkpoints such as COCOn may introduce limitations in scenarios requiring entirely novel dataset adaptations. Future enhancements could address these limitations by incorporating transfer learning techniques or leveraging larger, domain-specific datasets for further optimization.

IV. CONCLUSION AND RECOMMENDATION

This study devised multi-class dress code detection using Roboflow 3.0 Object Detection (Fast) model with COCOn checkpoint, able to achieve high accuracy (mAP 99.5%), precision (99.8%), and recall (100.0%). The model can identify and classify multiple dress codes sufficiently to meet the objectives of understanding and managing violations in dress codes. On the other hand, further iterations should entail adding more datasets and applying the newest advancements in object detection models to attain better accuracy, precision and recall.

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