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Detection and Classification of Dress Code Violations in Educational Environments Using Deep Learning

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Abstract: *This paper explores the utilization of deep learning techniques for the detection and classification of dress code violations in educational environments, identifying the challenges of manual enforcement and the potential for systems that are automated. This paper exhibits a model that integrates Faster R-CNN for detection and EfficientNet for classification, which provides an accurate and very efficient system to monitor students' compliance with the dress code policies. The model was trained on a dataset of images that were collected from Federal University Dutsin-Ma and were classified into "decent" and "indecent" dressing for both male and female students. The result achieved demonstrates that the model works efficiently, reaching a training accuracy of 98% and a validation accuracy of 96%, and with overall scores for precision, recall, and F1-score exceeding 97%, thereby proving its effectiveness in different dress code categories. The Uniformity across the techniques substantiates the feature extraction performance of the model and demonstrates its generalization ability. This paper outlines the benefits of automation in alleviating bias and human error by improving transparency and fairness and enforcing the dress code. The results showed how it is effective by combining powerful deep learning models with strong frameworks to solve problems of classification.*

Keywords: *Faster R-CNN, EfficientNet, Deep Learning, Dress Code Violation, Machine Learning*

1. INTRODUCTION

Dress codes are adopted to ensure security, order, and a conducive learning atmosphere in all school levels because of the increasing focus on the academic community's appearance. As [1] suggested, having a closer look at these dress codes might lead to the demonstration of bias toward socioeconomic status, subtype, gender, and race. Even though the reason provided for the dress codes often touts the intention of delivering professionalism and evading distractions, these objectives risk unfair and unbalanced treatment of individuals from diverse backgrounds [2]. As a result of this, dress code violations in schools can stimulate greater controversy due to the ongoing struggle between personal expression and the standard of institutional expectation [3].

Deep learning techniques have rapidly developed recently, and new methods of addressing and detecting dress code violations have been deployed. Machine learning models have shown robustness in diverse educational environments, where they serve to examine the behaviors of students and recognize relevant features based on existing criteria [4]. Machine learning techniques can be tailored to precisely identify indecent dressing in schools, therefore allowing students to be treated equally and impartially towards the dress code policies, as seen in other applications. The combined technologies help improve compliance monitoring and deeper understanding and predicting support of the complexities of the dress code violations and its influence on the educational environment [5].

By the use of sophisticated algorithms, educational settings can identify patterns and trends to track and analyze dress code violations. This technology can help them implement policies that are more universal of the diverse identities of the population of the students. The advancement of the deep learning models to identify and recognize dress code violations serves the purpose of fostering and elevating the overall student experience and allowing students to enjoy their freedom of expression while still maintaining the academic dress code integrity.

This study's technology largely emphasizes the surveillance and enforcement of dress code regulations for stationary individuals, such as students who are seated or standing in a given environment. The detection method is tailored for stationary people, facilitating clearer and more precise recognition of clothing components. This approach utilizes image processing and machine learning algorithms to examine static images in a specified area.

This study defines a decent clothing code by integrating both style and material in accordance with specified institutional criteria. Prohibited apparel encompasses garments deemed unsuitable for the environment, including overly casual materials and items featuring logos, designs, or prints that violate the dress code. Furthermore, fashion trends characterized by excessively revealing or unprofessional attire may be considered indecent. The systems will employ image recognition algorithms trained on various clothing styles and materials to differentiate between acceptable and unacceptable attire. These algorithms can identify fabric patterns and detect specific cuts, colors, or garment kinds that violate the dress code. The system analyzes visual data to enable consistent and precise identification of dress code infractions, adhering to institutional requirements while considering both material and stylistic elements.

This research creates an AI-driven model that is capable of monitoring dress code offenses on campuses. Automation of dress code offense detection is an issue of utmost concern in tertiary institutions globally, and Federal University Dutsin-Ma is not an exception to such societal vices. The manual or traditional method practiced by most of the campuses in ensuring strict adherence to dress code compliance is time-consuming, susceptible to human errors, and lacks precision. The traditional computer vision methods hence restrict their applicability in real-world settings where transparency in decision-making is necessary [6]. However, there is a dire need to address the problems briefly outlined by devising a more stable system that ensures a high level of moral decorum by students in academic institutions.

A study by Fakunle et al. [7] designed using deep learning techniques an automated real-time system for dress code compliance recognition. The model uses YOLOv4 for classifying and detecting clothing in their predefined categories for appropriately dressed (APD) and not appropriately (NAPD) for both males and females. An accuracy of 89% for the training set and 82% for the validation set was achieved by the model. The deep learning-based model gives a foundation for automated dress code recognition in academic settings.

This study Abubakar et al. [8] introduces a deep learning framework to detect and classify dress code violations in schools. Using the efficient MobileNetV2, the model sorts attire into four categories. A major focus is on model interpretability, with explainable AI techniques like SHAP and gradient-based visualizations ensuring transparency. Achieving 100% accuracy in training and 90% accuracy in validation, the model shows strong performance for real-world use in academic settings. These results confirm its reliability and effectiveness for monitoring dress codes in schools.

This study Durgam & Jatoth, [9] demonstrated a real-time system for dress code detection utilizing MobileNetV2 on the NVIDIA Jetson Nano with transfer learning. The system is designed to track adherence policies in the business and educational settings. The categories of “allowed attire” and “not allowed attire” is the custom dataset that the model developed is trained on. He uses Edge Impulse for training and implementation on edge devices. The model achieves real-time processing with a very low latency. The MobileNetV2 model sustained high accuracy, with 99.3% for training and 98.68% for testing, making it trustworthy for application in real-time. The model is refined for efficient edge computing and is appropriate for detecting dress codes in the real world.

This paper by Bedeli et al. [10] proposes the recognition of clothing using some deep learning in the context of forensics, which mainly focuses on the classification of clothing for investigating criminals. The research leverages Convolutional Neural Networks, such as AlexNet and LeNet, to categorize features of clothing across datasets that are with images of high resolution, and surveillance clips wiith low-quality. The result showed a promising performance, with the Logo dataset attaining an accuracy of 75.4% and the Surveillance dataset attaining an accuracy of 75.3%. While there are existing challenges, especially with the Deep fashion dataset that has nuanced details, the model shows its capability in identifying various image qualities on clothing attributes, thereby proving impactful for forensic experts.

A study by Kowshik et al. [11] proposes a classification of dress codes for schools that is CNN-based. By using deep learning, the task of checking students’ dress code compliance is automated, eradicating manual effort. The CNN-based model used for this paper collected pictures of students and are taken as input for the categorical classes such as “formal dressing” and “informal dressing”.The model is seen to be accurate and can be deployed in practical scenarios such as school campuses and university gates. Issues such as handling various clothing styles and the requirement of a varied dataset for improved performance are also addressed in the paper. Generally, the suggested approach is an effective method to check school dress code adherence.

This paper by Agarwal et al. [12] used a pre-trained YOLOv4 to create a model using a transfer learning technique. This model recognizes shirts, blazers, and formal business dress codes in an educational environment. Its mean average precision of 81% makes its validation feasible for real-time applications. Through the use of CNN and YOLO algorithm, the model performance on simplifying the detection is great, while errors associated with manual inspections are minimized.

The study emphasized the efficacy of these systems in improving organizational efficiency. A study by Azizan & Zaini, [13] focused on enhancing safety in laboratory environments by developing a real-time video analysis system aimed at ensuring compliance with safety attire regulations, such as lab coats and face masks. By utilizing YOLOv3, Caffe, and Mobilenet models, the system achieved an impressive accuracy rate of 92% for lab coat detection and 81% for face mask identification.

The model described by Rebekah et al. [14]) uses digital image processing techniques, such as object detection algorithms and facial recognition, to evaluate adherence to the established dress code, such as wearing ID cards and suitable footwear. The system incorporates a Convolutional Neural Network for object detection and a technique for background reduction for motion detection in the surveillance frames. The edge detection method is what the model uses to enable object localization and segmentation in the pictures acquired.

2. MATERIALS AND METHOD

The methodology we used for our deep learning model for detecting the dress code, as shown in Figure 1, emulates a structured framework. The Data Collection is illustrating the category of classes for both boys' and girls' students for decent and indecent dressing code were gathered and preprocessed through a sequence of steps, including augmentation of data, and then we split images to two categories namely; training which takes 80%, and validation takes 20%, then passed in to a Deep Convolutional Neural Network.

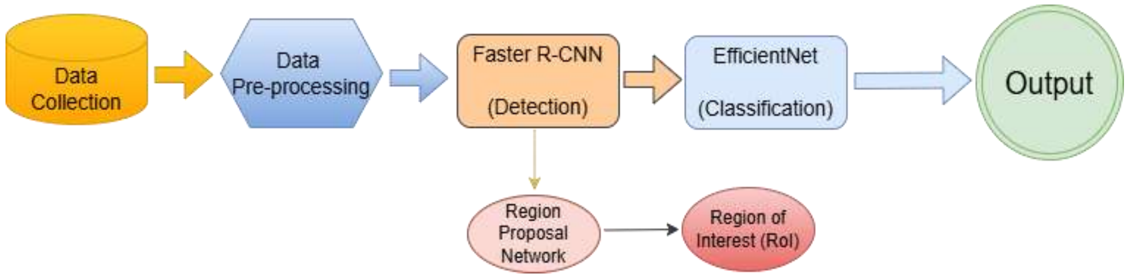

Figure 1: Proposed model architecture for dress code detection and classification

2.1 Data Collection

This dataset was collected from Federal University Dutsin-Ma, which consists of images of dress code for decent and indecent. A total number of 184 images were collected. The images are categorized into four classes, namely, "decent_boys_dressing", "decent_girls_dressing", "indecent_boys_dressing," and "indecent_girls_dressing," with 51 images of decent boys dressing, 53 images of decent girls dressing, 33 images of indecent boys dressing, and 49 images of indecent girls dressing. The images were sourced with an emphasis on preserving the various ways of dressing styles by students while complying with the dress code of the university's regulations.

Figure 2: Dress code dataset visualization

2.2 Data Pre-processing

After the collection of the dataset, then it will be the commencement of the pre-processing phase, incorporating many critical procedures that are designed to enhance the data quality and prepare it for input into the deep learning model. Primarily, data augmentation techniques are employed to create variations in the images and create an artificially extensive dataset. This method comprised random horizontal flipping, rotation, zoom, contrast modification, and translations, so replicating a wider array of real-world circumstances and improving the robustness of the model against different orientations slight aberrations in the images [15].

The images were resized to 512×512 pixels to ensure compatibility with the model architecture and to optimize computational efficiency. While EfficientNet-B0 typically uses a 224×224 pixel input size, resizing to 512×512 allowed for higher resolution and finer detail in the images, which was important for accurately detecting subtle differences in dress code violations. This size also balances the need for sufficient image detail while minimizing computational overhead during training and inference. The resizing is essential because deep learning models generally necessitate coherent dimensions input, and resizing the images ensured consistency in the data input.

After an extensive data augmentation, the total number of images amounts to 4,416, then the dataset was divided into a ratio of 80% for training with 3533 images and 20% for validation with 883 images. Figure 3 illustrates representative examples of the augmented dataset, demonstrating the variety of transformations applied including rotation, zoom, and horizontal flipping. This preparation stage established the groundwork for an effective and accurate deep learning model, ensuring training on a well-balanced dataset. The validation set was employed for the performance evaluation of the model during training in order to reduce overfitting, while the use of the training set is for the optimization of the model's parameters. This preparation stage established the groundwork for an impactful and accurate deep learning model, ensuring that the model was trained on a well-balanced dataset.

Figure 3: Example of an augmented image from the dataset

2.3 Model Training and Development

This study utilized CUDA version 11.3 and Torch version 1.10 for model training. The training procedure was executed on a high-performance workstation equipped with an NVIDIA T550 graphics card that possesses 4GB of DDR6 memory. The system had 16GB of RAM and a 512GB SSD for optimal storage and processing efficiency. Furthermore, it was equipped with an Intel Core 12th Generation i7 processor and functioned on the Windows 11 Pro 64-bit platform, providing a stable and optimum environment for deep learning activities.

Our proposed model, as shown in Figure 1, is a model framework for the task of detection and classification where the Faster R-CNN algorithm is used for detection and EfficientNet is used for classification. The process begins with an image that serves as an input, which is an image of the students in an academic environment. The image contains the student's clothes, which will be analysed for adherence to the dress code policy.

After that, the image gets passed into our first stage of the model, which serves as a Detection phase in the Faster R-CNN, where the algorithm serves as a two-stage framework for detection to categorize and detect dress code violations in academic environments accurately [16]. The Faster R-CNN object detection model utilizes a ResNet-50 backbone pre-trained on the COCO dataset. Initially, the backbone layers were frozen to retain the generic visual features learned from the large-scale dataset while training the region proposal network (RPN) and detection heads specific to the dress code detection task, after 10 epochs of training with the frozen backbone, the backbone was unfrozen to enable full fine-tuning of all layers. This allowed the model to adapt low-level and high-level feature representations to better capture dress code-specific visual cues.

During the initial frozen-backbone phase, a learning rate of 0.001 was used with the Adam optimizer. Once fine-tuning began with the unfrozen backbone, the learning rate was lowered to 0.0001 to allow more delicate weight adjustments and avoid disrupting the pre-trained features. And the training was performed using a batch size of 16 images per iteration, providing a balance between computational efficiency and gradient stability, given the image size of 512x512 pixels.

The Preliminary stage, Region Proposal Network (RPN), detects the important regions within the image that may include possible objects, such as students [17]. The Region Proposal Network generates candidate bounding boxes using a set of predefined anchor boxes. These anchors are carefully configured with multiple scales and aspect ratios tailored to the expected sizes and shapes of students in the images. Proper tuning of anchor box scales and ratios improves the accuracy of region proposals by better matching the target objects' dimensions, which is critical for effective detection in varying poses and distances [18]. The regions are outlined as bounding boxes to determine the presence of a student within a location and adjust the bounding boxes to include the student identified accurately. The refinement of the bounding box is accomplished by the regression Equation 1:

$$\check{y} = W \,.\, x + b \tag{1}$$

In this context, y is the predicted bounding box coordinates, W is the learned weight matrix, x symbolizes the extracted features from the image, and b is the bias term. The RPN helps in identifying students inside the image, constituting the preliminary phase in detecting dress code violations.

The second stage of Faster R-CNN employs Region of Interest Pooling (RoI) to extract Uniform-size feature maps from the region that RPN produced suggestions, adjusting their dimensions for uniform processing [19]. RoI pooling is critical for categorizing these locations as having a “decent dressing” or “indecent dressing” dress code. The result consists of bounding boxes surrounding the detected students, subsequently classified according to the adherence to the dress code. Faster R-CNN effectively detects and classifies dress code violations in academic environments by integrating the RPN for region recommendations.

EfficientNet CNN model classifies the detected student’s dress code efficiently. The entire EfficientNet-B3 model was fine-tuned end-to-end on the dress code dataset. This full fine-tuning allowed the model to adjust all layers, refining the learned features to distinguish “decent” versus “indecent” dress codes accurately, a learning rate of 0.001 was used with the Adam optimizer, supported by a learning rate decay schedule to reduce the rate progressively during training, enhancing convergence stability and performance. The batch size was set to 16, consistent with the detection model, optimizing the use of computational resources and training efficiency. After the Faster R-CNN identifies the student in the images, the EfficientNet classifies the cloth from the bounding boxes. EfficientNet has a high accuracy and low computational complexity, making it ideal to process huge amounts of data with resources that are limited [20]. The model performs very well by learning difficult dress features to identify between different styles. Based on the dress code adherence, EfficientNet categorizes dress codes. It classifies the dress code based on “decent dressing” or “indecent dressing”. EfficientNet accurately assesses the dress code adherence and categorizes it automatically, which makes it very reliable for use in the academic environment.

$$P(y_i) = \frac{e^{zi}}{\sum_{j=1}^{c} e^{zj}} \tag{2}$$

$P(y_i)$ represents the probability of the attire being classified into class y_i, where z^i is the raw output score for class i, C is the total number of classes (such as decent and indecent), and y_i denotes the class label (e.g., decent and indecent). The model proved robust in classifying unseen images. Performance metrics like accuracy, mAP (Mean Average Precision), precision, recall, and F1 score confirmed the model's ability to distinguish decent and indecent dress codes.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{3}$$

Precision measures the accuracy of positive predictions, or how many of the predicted positives are correct.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{4}$$

Recall measures how well the model identifies all relevant positive cases or the ability to detect all non-compliant attire (in this case).

$$F1\ Score = 2 \times \frac{Precision \times \mathrm{Recall}}{Precision + \mathrm{Recall}} \tag{5}$$

The F1 score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance when the data is imbalanced.

3. RESULTS AND DISCUSSIONS

In this section, we analyze our model’s training and evaluation results on the datasets. Performance metrics like precision, Mean Average Precision (mAP), recall, F1-score, accuracy and loss curves, and a confusion matrix are used to evaluate the model performance. These results demonstrate the learning behavior of the dress code detection violation of the model and class distinction, and the unseen data generalization. The following discussions relate these findings and address limitations.

Figure 4: Predicted dress codes (a) Decent boys dressing (b) Indecent boys dressing (c) Decent girls dressing (d) Indecent girls dressing

As shown in Figure 4, the model performs very well in classifying different dress codes; it accurately classifies the four categories of dress code well, with similar success for other images. These predictions show the ability of the model to differentiate between the categories, with some possible challenges in explicating the dress codes based on individual cultural norms. The green border bounding box around the images illustrates that the predictions the model made are successful.

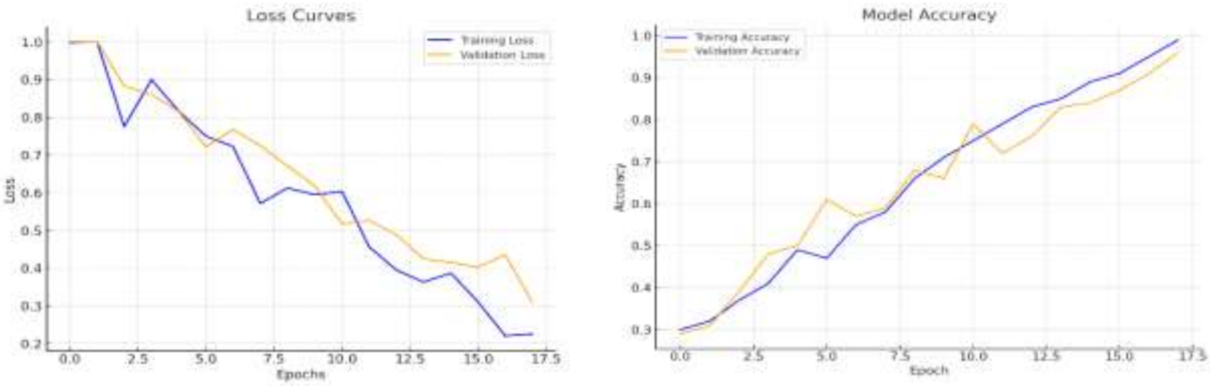

Figure 5: Loss vs Accuracy

The loss curve graph shows a steady decrease in both the training and in the validation loss, and this implies that the model is really learning progressively and its performance is improving over time. Nonetheless, with a consistent drop in both validation and training loss, the model will generalize flawlessly to unseen data. The model accuracy graph indicates a significant increase in both validation and training accuracy, achieving 98% in training and 96% in validation. This indicates that the model is performing effectively, exhibiting robust generalizability to validation data. Overall, the trends show that the model is improving throughout the epochs and learning seamlessly.

Table 1: Confusion matrix

True / Predicted Labels	Decent_Boys_Dressing	Decent_Girls_Dressing	Indecent_Boys_Dressing	Indecent_Girls_Dressing
Decent_Boys_Dressing	12	0	0	0
Decent_Girls_Dressing	0	12	0	0
Indecent_Boys_Dressing	0	0	7	1
Indecent_Girls_Dressing	0	0	1	9

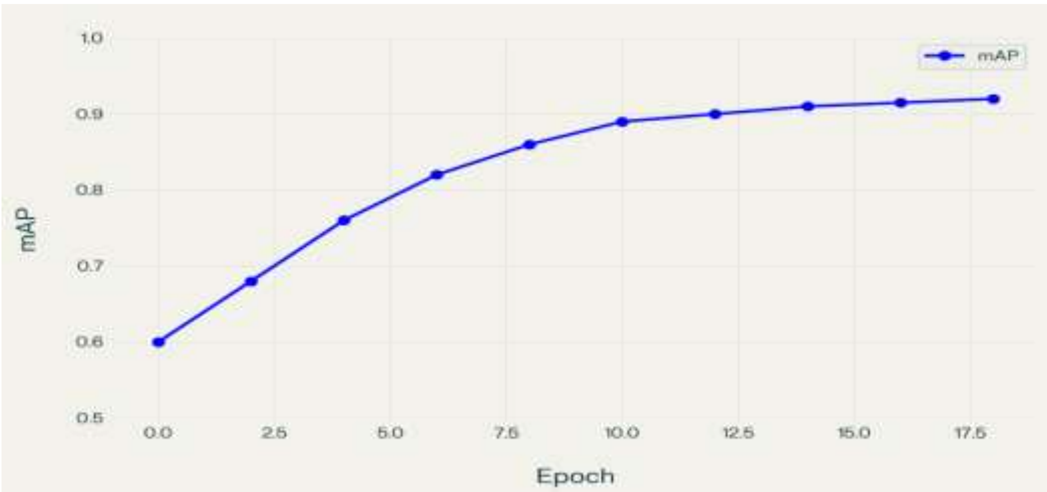

Figure 6: Mean average precision

The model demonstrates superior performance in all of the four categories. It accurately predicts all the instances of the "decent_boys_dressing" and "indecent_girls_dressing", attaining without any misclassifications 12 correct predictions. The model accurately classifies 7 instances of "indecent_boys_dressing", which have 1 misclassification. Likewise, "indecent_girls_dressing" shows accurately 9 predictions with also 1 misclassification. The model reveals robust performance with minor errors, particularly in the "decent" categories, and a small number of misclassifications in the "indecent" categories. As shown in Table 2, the confusion matrix shows the generalizability of the model across various classes effectively.

The mean Average Precision (mAP) progression graph as shown in Figure 6, demonstrates how the performance of the Faster R-CNN detection model improves over 20 training epochs. Starting at around 60% in the first epoch, this initial mAP reflects the use of pre-trained weights from the COCO dataset before fine-tuning on the dress code detection task, demonstrating the strength of transfer learning as a starting point. As training continues, the mAP steadily increases due to fine-tuning, which involves unfreezing the ResNet-50 backbone and further training the region proposal network and detection heads to capture the specific features of student attire better. By the later epochs, the curve flattens and plateaus near 92%, indicating that the model has effectively learned to detect dress code violations with high accuracy and has reached convergence without overfitting. Minor fluctuations along the way are expected due to training dynamics like batch sampling and learning rate changes, but overall, the smooth upward trend reflects a well-designed and stable training process.

Table 2: Performance metrics

Class	Precision	Recall	F1-Score
Decent Boys	98%	98%	98%
Decent Girls	98%	98%	98%
Indecent Boys	97%	97%	97%
Indecent Girls	97%	97%	97%

The model exhibits exceptional performance across all four classes, achieving precision, recall, and F1 scores of more than 97%. It demonstrates exceptional performance in the Decent Boys and Decent Girls categories, achieving 98% across all metrics, indicating high precision in differentiating these classifications. Even for the more difficult Indecent Boys and Indecent Girls, it sustains a high 97%, signifying strong generalization. The uniformity of elevated scores across all categories underscores the model's proficiency in reducing false positives and false negatives, managing class imbalances adeptly, and generalizing effectively, notwithstanding minor declines in performance for the "Indecent" classes attributable to intrinsic classification challenges.

These predictions demonstrate the model's ability to differentiate between the four dress code categories within the specific cultural context of Federal University Dutsin-Ma. However, this capability raises significant concerns regarding cross-cultural applicability and the subjective nature of dress code interpretation. The concepts of 'decent' and 'indecent' dressing are deeply embedded in cultural, religious, and social contexts that vary significantly across different societies. What may be considered appropriate attire in one cultural setting could be deemed inappropriate in another, and vice versa. This cultural specificity poses several critical challenges: (1) Algorithm bias toward specific cultural norms may result in discriminatory outcomes when applied to diverse populations; (2) The binary classification into 'decent' and 'indecent' categories oversimplifies the nuanced spectrum of cultural dress expectations; (3) Individual expression and religious dress requirements may be inappropriately flagged by systems trained on narrow cultural datasets. These limitations underscore the necessity for culturally-sensitive model development, extensive consultation with diverse stakeholders, and implementation frameworks that allow for cultural customization and human oversight in decision-making processes.

4. CONCLUSION

Deep learning technology for dress code monitoring in schools raises ethical issues of privacy, fairness, and student autonomy. Our data handling protocols ensure images are securely stored and used exclusively for dress code enforcement, complying with relevant data protection laws, and communicating data use policies to stakeholders to protect privacy. The model was trained on a diverse dataset of cultural and gender-based attire styles to reduce bias and promote fairness. Educators must review automated detections to provide context and uphold students' freedom of expression. To ensure accountability and confidence, we actively engage kids, parents, and school officials throughout implementation, obtaining informed permission and encouraging open discourse. Technology developers, ethics committees, and regulatory authorities collaborate to maintain ethical supervision and refinement. These initiatives strive to create a fair and inclusive academic atmosphere by balancing appropriate dress code enforcement with individual liberties.

In conclusion, this study successfully develops a deep learning model that automates the classification and detection of dress code violations in educational environments. Using Faster R-CNN for detection and EfficientNet for classification, the model shows remarkable accuracy, precision, recall, and F1-scores across all four categories: *Decent_Boys_Dressing, Decent_Girls_Dressing, Indecent_Boys_Dressing, and Indecent_Girls_Dressing*. The model offers a more coherent, transparent, and just approach to imposing dress code policies, minimizing human errors and bias by automating the monitoring process. However, a key limitation is the vulnerability of the model to individuals with clarification of "decent" versus "indecent" dress code, which varies across cultural and individual situations, and a lack of an ample dataset is also another limitation. Future research could focus on improving the adaptability of the model to different cultural norms by incorporating more diverse datasets and refining the model to better handle the individual classifications and transparency in real-world applications, and also focus on adapting the system to focus on mobile subjects by incorporating video streams and dynamic image processing algorithms.

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