International Journal of Innovative Information Systems & Technology Research 14(3):153-163, July-Sept, 2026

© SEAHI PUBLICATIONS, 2026 www.seahipublications.org **ISSN: 2467-8562**

DOI:10.5281/zenodo.21614246

Automated Detection of Dress-Code Compliance in Smart Campus Environments Using Deep Transfer Learning

Benisemeni Esther Zakka; Muhammed Kuliya; Mohammed Abdullahi Bawa & Gloria Ngozi Jola

Federal Polytechnic, Bauchi, Nigeria

ABSTRACT

The enforcement of institutional dress codes in higher education institutions is traditionally carried out through manual monitoring, which is often labor-intensive, subjective, and difficult to implement consistently across large student populations. This study presents an automated image-based framework for dress-code compliance detection using deep transfer learning. A dataset comprising 8,713 labeled images, including 4,618 dress-code compliant and 4,095 dress-code non-compliant images, was developed based on institutional dress-code guidelines. Prior to model training, the images were preprocessed through resizing, normalization, and data augmentation to improve data consistency and model generalization. A ResNet-50 convolutional neural network initialized with pretrained ImageNet weights was adopted using transfer learning to classify images into compliant and non-compliant categories. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results showed that the proposed model achieved an overall classification accuracy of 98.45%, with consistently high precision, recall, and F1-score, demonstrating its ability to accurately distinguish between dress-code compliant and non-compliant attire. Analysis of the learning curves further indicated stable convergence and good generalization, while the confusion matrix revealed only a small number of misclassifications. These findings demonstrate that deep transfer learning provides an accurate, scalable, and reliable solution for automated dress-code compliance monitoring in smart campus environments. The proposed framework has the potential to support institutional policy implementation by providing objective decision support while reducing the limitations associated with manual monitoring. Future work will focus on real-time deployment, cross-institutional evaluation, and improving model robustness under diverse environmental conditions.

Keywords: Deep Learning ,Image classification ,Dress-Code Compliance ,ResNet-50 ,Transfer Learning ,Smart Campus

1 INTRODUCTION

Dress-code regulation remains a persistent challenge in many higher education institutions, particularly within developing educational systems where large student populations make manual enforcement difficult. Studies have reported a growing prevalence of non-compliant dressing among undergraduate students in Nigerian tertiary institutions, raising concerns about professionalism, institutional image, and the overall learning environment (Juliet and Emeka 2020) (Cordelia et al. 2018). Conventional enforcement methods rely primarily on manual monitoring by institutional personnel, a process that is often labour-intensive, subjective, and inconsistent across different observers. These limitations reduce

the effectiveness of dress-code enforcement and highlight the need for more objective and scalable monitoring approaches.

In recent years, rapid advancements in artificial intelligence (AI), particularly in machine learning and deep learning, have significantly transformed the field of computer vision. Image recognition systems now achieve remarkable performance in tasks such as object detection, facial recognition, surveillance monitoring, and pattern classification (Chauhan et al. 2018); (LeCun et al. 2018). These technologies have found widespread applications in diverse domains, including security systems, intelligent surveillance, smart environments, healthcare, and fashion analysis (Chang and Zhang 2022). Their ability to automatically learn discriminative visual features from large datasets makes them well suited for solving complex image classification problems.

Within the fashion and apparel domain, computer vision techniques have been successfully applied to clothing recognition, style classification, and garment analysis (Chang and Zhang 2022). In particular, Convolutional Neural Networks (CNNs) have demonstrated outstanding capability in learning hierarchical representations of visual characteristics such as texture, colour, shape, and clothing patterns, making them highly effective for apparel classification tasks (Chauhan et al. 2018). Furthermore, deep learning architectures such as Residual Networks (ResNet) address the challenges associated with training very deep neural networks by mitigating the vanishing gradient problem and improving feature reuse, thereby enhancing classification performance (LeCun et al. 2018).

Despite these advances, the application of deep learning techniques to automated dress-code compliance detection within higher education institutions remains relatively underexplored. Existing studies on indecent dressing in Nigerian campuses have primarily focused on sociological, cultural, and behavioural perspectives (Juliet and Emeka 2020);(Oyewumi 2018), with limited attention given to automated technology-driven solutions. Although recent studies have explored the use of machine learning techniques, including Convolutional Neural Networks, Support Vector Machines, and hybrid deep learning models, these approaches are often constrained by limited datasets, relatively shallow architectures, or the absence of transfer learning strategies (Adebiyi and Obagbuwa 2021); (Akande et al. 2020). Consequently, there remains a need for robust deep learning models capable of providing accurate and scalable dress-code compliance detection within institutional environments.

To address this gap, this study proposes an automated image-based dress-code compliance detection framework using deep transfer learning. The problem is formulated as a supervised binary image classification task that distinguishes between dress-code compliant and dress-code non-compliant attire based on predefined institutional guidelines. A ResNet-50 deep convolutional neural network is employed using transfer learning, where pretrained ImageNet weights are utilized to improve feature extraction, enhance model generalization, and reduce training complexity (LeCun et al. 2018).

A dataset comprising 8,713 labeled images was developed for model training and evaluation, capturing a wide variety of clothing styles and environmental conditions. The performance of the proposed model is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis, to provide a comprehensive assessment of its effectiveness in distinguishing between compliant and non-compliant attire (Chauhan et al. 2018).

This study contributes to the development of intelligent campus management systems by demonstrating the feasibility of applying deep transfer learning to automated dress-code compliance detection. Specifically, the study develops a labeled image dataset for institutional dress-code classification, implements a ResNet-50 transfer learning model for automated image classification, and evaluates its performance using standard machine learning metrics. In addition, ethical issues relating to privacy, algorithmic bias, and cultural sensitivity are acknowledged, thereby supporting the responsible application of artificial intelligence in institutional policy enforcement (Smith 2022).

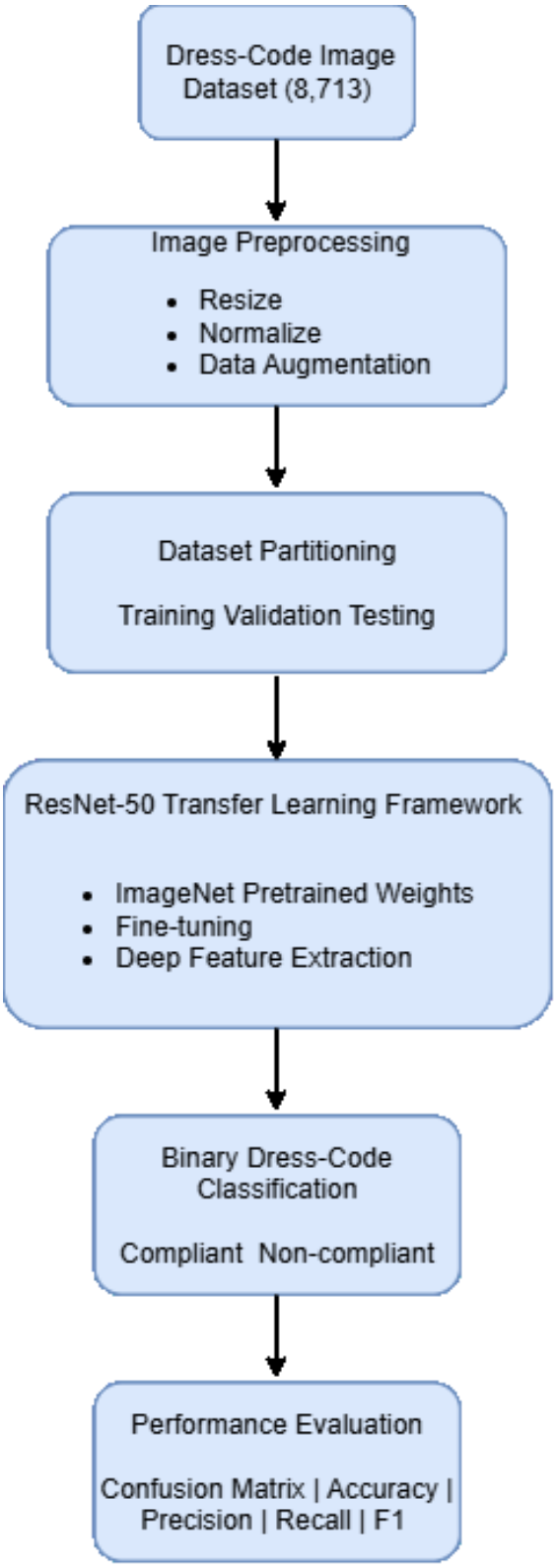
2 RELATED WORK

Research on dress-code regulation within academic environments has traditionally been examined from sociological, cultural, and behavioral perspectives. Several studies have documented the prevalence of non-

compliant dressing among undergraduate students in Nigerian tertiary institutions, emphasizing its perceived impact on institutional image, student behavior, and academic culture (Juliet and Emeka 2020); (Cordelia et al. 2018);(Oyewumi 2018). While these works provide important contextual understanding, they primarily rely on qualitative analysis and manual enforcement mechanisms, offering limited insight into automated or technology-driven solutions. With the advancement of machine learning and computer vision, image-based classification techniques have increasingly been applied to problems involving human appearance and behavior. Convolutional Neural Networks (CNNs) have emerged as the dominant approach for image recognition and object detection tasks due to their ability to automatically learn hierarchical feature representations from raw pixel data (Chauhan et al. 2018). Deep learning models have achieved state-of-the-art performance in applications such as facial recognition, surveillance systems, and visual attribute classification (LeCun et al. 2018). In the fashion and apparel domain, computer vision techniques have been successfully employed for clothing recognition, style classification, and garment analysis. (Chang and Zhang 2022) demonstrated the effectiveness of deep learning models for clothing style recognition, highlighting the suitability of CNN-based architectures for capturing texture, color, and structural features of garments. These studies establish a technical foundation for applying deep learning to clothing-related classification tasks but do not explicitly address institutional dress-code compliance. Several recent studies have attempted to apply machine learning techniques to the detection of indecent or non-compliant dressing within campus environments. Adebiyi and Obagbuwa (Adebiyi and Obagbuwa 2021) developed a CNN-based model for indecent dressing detection and reported promising classification accuracy. Similarly, Akande (Akande et al. 2020) proposed a deep learning framework combining convolutional and sequential models, achieving improved detection performance. Other approaches have explored traditional machine learning algorithms such as Support Vector Machines (SVMs) and Random Forests for indecent dressing classification, though these methods generally exhibit lower accuracy and limited scalability compared to deep learning models (Ogunseye et al. 2021); (Adetunji and Ajibade 2021) Despite these contributions, several limitations remain evident in existing studies. Many approaches rely on relatively small or homogeneous datasets, which restrict model generalization across diverse clothing styles and environmental conditions. Additionally, a number of studies employ shallow architectures or train deep networks from scratch, leading to increased training complexity and susceptibility to overfitting. The absence of transfer learning strategies in some works further limits the ability of models to leverage pretrained visual representations. Transfer learning using deep residual networks has proven effective in addressing these challenges across various computer vision tasks. Residual architectures such as ResNet mitigate the vanishing gradient problem and enable the training of very deep networks with improved convergence properties (LeCun et al. 2018). By leveraging pretrained weights from large-scale datasets such as ImageNet, transfer learning allows models to achieve high performance even when task-specific datasets are relatively limited. In contrast to prior work, this study adopts a ResNet-50–based transfer learning framework for dress-code compliance detection, supported by a relatively large and diverse dataset. The proposed approach emphasizes robust feature extraction, systematic evaluation using multiple performance metrics, and ethical considerations related to appearance-based classification. By addressing dataset scale, model depth, and generalization capability, this work advances existing research on automated dress-code compliance systems within smart campus environments.

3 METHODOLOGY

This study proposes an automated image-based framework for detecting dress-code compliance using deep transfer learning. The methodology consists of five major stages: dataset preparation, image preprocessing, transfer learning using ResNet-50, model training, and performance evaluation. Figure 1 illustrates the overall workflow of the proposed system.



Overall workflow of the proposed dress-code compliance detection framework.

3.1 Problem Formulation

The dress-code compliance detection task is formulated as a supervised binary image classification problem. Given an input image

$x \in R^{H \times W \times C}$,

the objective is to learn a mapping

$f(x;\theta): R^{H \times W \times C} \rightarrow \{0,1\}$,

where class 0 represents dress-code non-compliant (indecent) dressing and class 1 represents dress-code compliant (decent) dressing. The parameters θ are learned during training by minimizing the binary classification loss.

3.2 Dataset

A custom image dataset was developed for training and evaluating the proposed model. The dataset contains a total of 8,713 labelled images collected from publicly available image sources and controlled image acquisition. The images represent diverse clothing styles, body poses, illumination conditions, and background environments to improve model generalization.

The dataset comprises two classes:

- Dress-code compliant (decent): 4,618 images
- Dress-code non-compliant (indecent): 4,095 images

Each image was labelled according to predefined institutional dress-code guidelines. The relatively balanced class distribution reduces classification bias during model training.

The dataset was partitioned into training, validation, and testing subsets for model development and evaluation. The training subset was used for learning the model parameters, the validation subset was used to monitor model performance during training and guide hyperparameter tuning, while the testing subset was reserved exclusively for the final performance evaluation. The training set was used for model learning, the validation set for monitoring convergence and hyperparameter tuning, while the testing set was reserved for final performance evaluation.

3.3 Image Preprocessing

Prior to training, all images underwent preprocessing to ensure uniformity and improve learning performance. Images were resized to a fixed spatial resolution compatible with the ResNet-50 architecture before training. Pixel intensity values were normalized to the interval $[0,1]$ by dividing each pixel value by 255.

To improve model robustness and reduce overfitting, data augmentation techniques were applied to the training images. These included random horizontal flipping, small-angle rotation, and minor scaling transformations. Data augmentation increases sample diversity and enables the model to learn invariant visual features associated with dress-code compliance.

3.4 Transfer Learning Using ResNet-50

The proposed framework employs ResNet-50, a deep residual convolutional neural network consisting of fifty layers. ResNet-50 introduces residual skip connections that alleviate the vanishing gradient problem and facilitate the training of deep neural networks.

Transfer learning was adopted by initializing the network with weights pre-trained on the ImageNet dataset. The original classification layer was replaced with task-specific fully connected layers for binary dress-code classification. A dense layer containing 128 neurons with Rectified Linear Unit (ReLU) activation was added, followed by a sigmoid output neuron that predicts the probability of an image belonging to the compliant class.

By leveraging pretrained visual features, transfer learning reduces training time while improving feature extraction and model generalization.

3.5 Model Training

The proposed model was implemented using the TensorFlow Keras deep learning framework. Binary cross-entropy was adopted as the objective loss function because the problem involves binary classification.

The loss function is expressed as

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)],$$

where y_i denotes the true class label, $\hat{y}_i$ represents the predicted probability, and N is the number of training samples.

Model optimization was performed using the Adam optimizer, which adaptively updates the learning rate during training to accelerate convergence and improve optimization stability.

3.6 Performance Evaluation

The predictive performance of the proposed ResNet-50 model was evaluated using Accuracy, Precision, Recall, F1-score, and confusion matrix analysis.

Accuracy measures the proportion of correctly classified samples and is computed as

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

where TP, TN, FP, and FN denote the numbers of true positives, true negatives, false positives, and false negatives, respectively.

Precision is computed as

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

Recall is given by

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

while the F1-score is calculated as

$$F1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right).$$

In addition to the evaluation metrics, a confusion matrix was generated from the test dataset to provide a detailed analysis of the classification performance. The confusion matrix served as the basis for interpreting the numbers of correctly and incorrectly classified compliant and non-compliant images and for validating the computed performance metrics.

4 EXPERIMENTAL RESULTS AND ANALYSIS

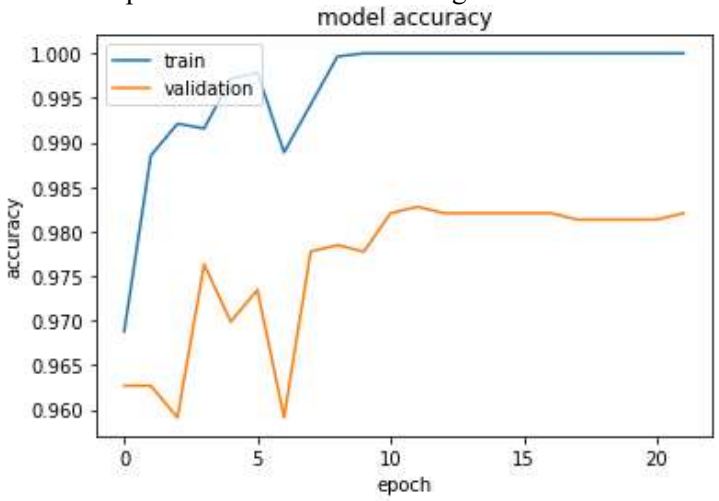
4.1 Learning Behaviour of the Proposed Model

The learning behaviour of the proposed ResNet-50 model was examined using the training and validation accuracy and loss curves obtained during the training process. These learning curves provide valuable insight into the convergence characteristics of the network, its learning stability, and its ability to generalize to unseen images.

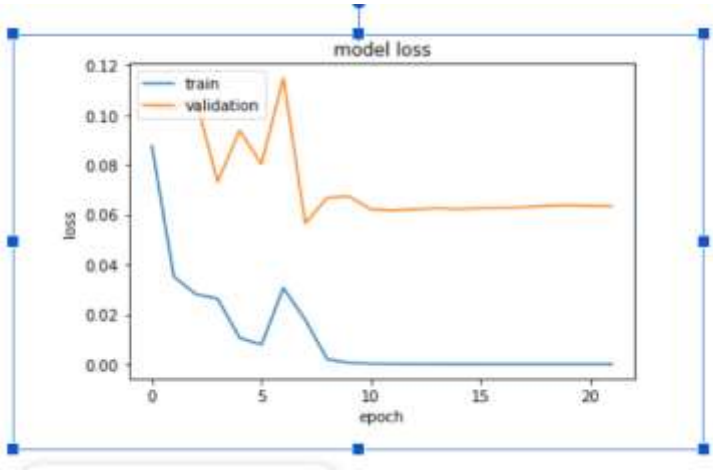
Figure 2 presents the training and validation accuracy curves. The training accuracy increased steadily throughout the training process and gradually converged toward the validation accuracy, indicating that the model successfully learned discriminative features associated with dress-code compliant and non-compliant attire. Although minor fluctuations were observed during the early training epochs, both curves stabilized as training progressed, suggesting effective optimization and good generalization performance.

Similarly, Figure 3 illustrates the corresponding training and validation loss curves. The training loss consistently decreased with increasing epochs, while the validation loss followed a similar downward trend with only slight variations. The relatively small gap between the training and validation loss curves indicates that the proposed model did not suffer from significant overfitting. Instead, the learning process remained stable and converged smoothly, demonstrating the effectiveness of transfer learning in adapting the pretrained ResNet-50 architecture to the dress-code compliance classification task.

Overall, the learning curves indicate that the proposed model achieved stable convergence, effective feature learning, and strong generalization capability, providing a solid foundation for the high classification performance obtained during model evaluation.



Training and validation accuracy curves of the proposed ResNet-50 model.



Training and validation loss curves of the proposed ResNet-50 model.

4.2 Quantitative Performance Evaluation

Table 1 summarizes the classification performance of the proposed ResNet-50 model on the test dataset. The model achieved an overall classification accuracy of 98.45%, demonstrating its effectiveness in distinguishing between dress-code compliant and non-compliant images. The consistently high values of precision, recall, and F1-score further indicate that the model produced reliable predictions while maintaining a balanced classification performance across both classes.

The high precision shows that the model generated very few false positive predictions, while the high recall indicates that most compliant and non-compliant dressing instances were correctly identified.

Similarly, the F1-score demonstrates a strong balance between precision and recall, confirming that the proposed framework is both accurate and robust for automated dress-code compliance detection.

Performance evaluation of the proposed ResNet-50 model.

Metric	Value
Accuracy	98.45%
Precision	98.46%
Recall	98.44%
F1-score	98.44%

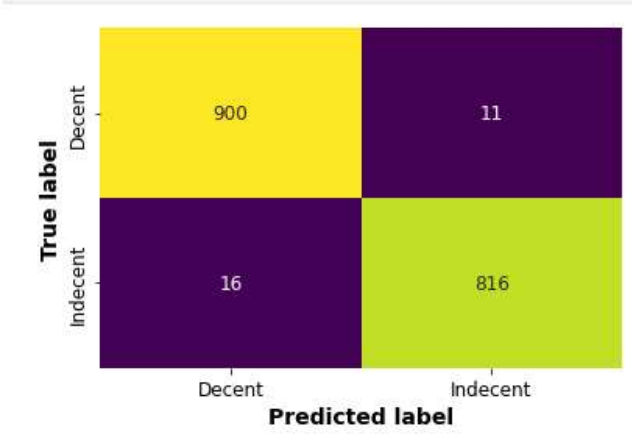
4.3 Confusion Matrix Analysis

The confusion matrix shown in Figure 4 provides a detailed evaluation of the classification performance of the proposed ResNet-50 model. It summarizes the relationship between the predicted and actual class labels, thereby revealing the model's ability to correctly distinguish between dress-code compliant and non-compliant images.

The model correctly classified 900 compliant images and 816 non-compliant images, while only 11 compliant images were incorrectly classified as non-compliant and 16 non-compliant images were misclassified as compliant. These results correspond to an overall classification accuracy of 98.45%, indicating excellent predictive performance with very few classification errors.

The strong diagonal dominance observed in the confusion matrix demonstrates that the learned feature representations effectively separate the two dress-code categories. The small number of off-diagonal entries suggests that the few misclassifications are likely associated with visually ambiguous images, challenging lighting conditions, partial occlusion, or clothing styles that share similar visual characteristics across the two classes.

Overall, the confusion matrix confirms that the proposed transfer learning framework provides reliable and consistent classification performance, making it suitable for supporting automated dress-code compliance monitoring in smart campus environments.



Confusion matrix of the proposed ResNet-50 model.

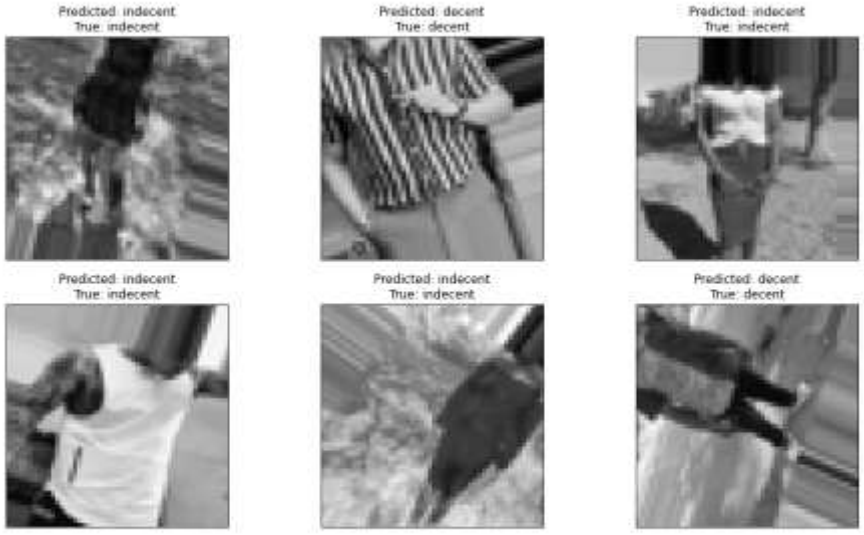
4.4 Sample Prediction Results

To further demonstrate the effectiveness of the proposed model, representative prediction results obtained from the test dataset are presented in Figure 5. The examples include correctly classified dress-code compliant and non-compliant images, illustrating the model's ability to distinguish between the two categories under varying clothing styles and imaging conditions.

The prediction results show that the proposed ResNet-50 model successfully identified compliant dressing based on institutional dress-code requirements while accurately detecting images that violated

the prescribed dress code. The correct classification of these representative samples is consistent with the high quantitative performance reported in the previous subsections.

Although the model performed exceptionally well, a small number of misclassifications were observed during testing, as reflected in the confusion matrix. These errors are likely attributable to challenging visual conditions such as complex backgrounds, variations in illumination, partial occlusion, or clothing styles exhibiting characteristics common to both compliant and non-compliant categories. Nevertheless, the low number of misclassified samples demonstrates the robustness and reliability of the proposed framework for automated dress-code compliance detection.



Representative prediction results of the proposed ResNet-50 model showing correctly classified dress-code compliant and non-compliant images.

4.5 Discussion

The experimental results demonstrate that transfer learning using the ResNet-50 architecture provides an effective solution for automated dress-code compliance detection. The learning curves showed stable convergence during training, with only a small gap between the training and validation performance, indicating that the model generalized well to unseen images without significant overfitting. This behaviour reflects the effectiveness of transfer learning in adapting pretrained visual representations to the dress-code classification task.

The proposed model achieved an overall classification accuracy of 98.45%, accompanied by consistently high precision, recall, and F1-score values. The confusion matrix further confirmed that the model correctly classified the majority of both compliant and non-compliant dressing images, with only a small number of false positive and false negative predictions. These findings suggest that the learned feature representations effectively capture the visual characteristics that distinguish the two dress-code categories.

The high classification performance can largely be attributed to the residual learning mechanism employed by ResNet-50. By incorporating skip connections, the network is able to preserve feature information across multiple layers, enabling the extraction of both low-level visual features, such as colour and texture, and higher-level semantic features related to clothing style and appearance. Furthermore, the use of transfer learning with pretrained ImageNet weights improved feature extraction and accelerated model convergence despite the relatively limited size of the application-specific dataset.

The findings are consistent with previous studies that have demonstrated the effectiveness of deep convolutional neural networks and transfer learning for image classification tasks in surveillance, apparel recognition, and related computer vision applications. However, unlike many earlier studies that relied on smaller datasets or shallower network architectures, the proposed framework combines a relatively large

labelled dataset with a deep residual network, resulting in improved classification performance and stronger generalization capability.

From a practical perspective, the proposed framework has considerable potential for supporting intelligent campus management systems. Automated dress-code compliance detection can complement existing institutional monitoring practices by providing objective, consistent, and scalable assessment of dress-code adherence. Rather than replacing human decision-making, such systems can serve as decision-support tools that improve monitoring efficiency while reducing observer bias. Nevertheless, practical deployment should be accompanied by appropriate safeguards relating to privacy, transparency, fairness, and institutional policy to ensure the responsible application of artificial intelligence within educational environments.

5 CONCLUSION AND FUTURE WORK

This study presented an automated framework for dress-code compliance detection in smart campus environments using deep transfer learning. The proposed approach formulates dress-code assessment as a supervised binary image classification problem and employs a ResNet-50 convolutional neural network initialized with pretrained ImageNet weights to distinguish between dress-code compliant and non-compliant attire.

A custom dataset containing 8,713 labelled images was developed to train and evaluate the proposed model. Experimental evaluation demonstrated that the framework achieved an overall classification accuracy of 98.45%, with consistently high precision, recall, and F1-score values. The confusion matrix further showed that only a small number of images were incorrectly classified, indicating that the proposed model effectively learned discriminative visual features for separating the two dress-code categories. The training and validation learning curves also exhibited stable convergence with no significant evidence of overfitting, demonstrating the effectiveness of transfer learning for this application.

The findings suggest that deep transfer learning provides a practical and reliable approach for supporting automated dress-code monitoring within higher education institutions. Rather than replacing existing institutional procedures, the proposed framework can serve as an intelligent decision-support tool that promotes greater consistency, scalability, and objectivity in dress-code enforcement.

Despite the promising performance, this study has some limitations. The model was developed for binary classification based on a single institutional dress-code policy, and its performance may vary when applied to institutions with different cultural or regulatory requirements. Furthermore, the framework operates on still images and does not exploit temporal information available in video-based surveillance systems.

Future research should investigate multi-class dress-code classification capable of identifying specific categories of dress-code violations, evaluate the framework using datasets collected from multiple institutions, and explore lightweight deep learning architectures suitable for real-time deployment on edge devices. Additional work on explainable artificial intelligence, fairness-aware learning, and privacy-preserving computer vision techniques will also be important for ensuring transparent, ethical, and responsible deployment within smart campus environments.

REFERENCES

Adebiyi, O. A., and I. C. Obagbuwa. 2021. “Indecent Dressing Detection Using Convolutional Neural Network.” *Proceedings of the 4th International Conference on Computer Science Application Engineering*, 369–74.

Adetunji, O., and F. Ajibade. 2021. “Machine Learning Model for Indecent Dressing Detection in a Campus Environment.” *Computer Science and Technology*, 25–32.

Akande, O., A. O. Akinola, and E. O. Omidiora. 2020. “Deep Learning Approach to Detecting Indecent Dressing in Campus.” *International Journal of Advanced Computer Science Applications*, 469–75.

Chang, Y.-H., and Y.-Y. Zhang. 2022. "Deep Learning for Clothing Style Recognition Using YOLOv5." *Micromachines*, 12–34.

Chauhan, K., K. K. Ghanshala, and R. Johi. 2018. "Convolutional Neural Network (CNN) for Image Detection and Recognition." *2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC)* (India).

Cordelia, C. A., P. Egboka, and I. Aneirobi Elizabeth. 2018. *Indecent Dressing Among Female Undergraduates of Nnamdi Azikiwe University: Types, Sustaining Factors and Implications for Rebranding Nigeria Agenda*.

Juliet, O. O., and U. Emeka. 2020. "Indecent Dressing Among Undergraduate Students in Nigerian Tertiary Institutions: Implications for Counselling." *Unizik Journal of Educational Research and Policy Studies*, 23.

LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. 2018. *Deep Learning*. Macmillan Publishers Limited.

Ogunseye, O. O., O. M. Olaniyi, and O. O. Ogundele. 2021. "Indecent Dressing Using Support Vector Machine Algorithm." *Journal of Computer Science and Its Application*, 1–9.

Oyewumi, O. 2018. "Indecent Dressing and Its Implications on the Moral Standards of Tertiary Institution Students." *Journal of Educational and Social Research*, 117–24.

Smith, J. 2022. *The Ethics of Collecting Data on Clothing Choices*.