

AI-BASED CLASSIFICATION OF SCHOOL STUDENT NEATNESS USING CONVOLUTIONAL NEURAL NETWORK (CNN)

Andi Saryoko^{1*}; Hanna Rizkia¹

Informatics¹

Universitas Nusa Mandiri, Jakarta, Indonesia¹

<https://nusamandiri.ac.id>¹

andi.asy@nusamandiri.ac.id*, hanna_2122@nusamandiri.ac.id

(*) Corresponding Author

(Responsible for the Quality of Paper Content)



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Abstract— The neatness of students in Scouting uniforms is a form of implementation of discipline that reflects compliance with school rules. At SDIT Ajimutu Global Insani, the uniform attributes assessed include the completeness of the Scout uniform. The neatness in wearing these attributes greatly supports the creation of an orderly and conducive learning environment. This study aims to classify the level of neatness of Scouting uniforms automatically using an artificial intelligence-based approach. The data used are in the form of student images recorded using a Canon EOS 60D DSLR camera, with a total data of 510 images, consisting of 88 female students and 82 male students. The method used in this study is Convolutional Neural Network (CNN) with a transfer learning approach using the MobileNetV2 architecture with Transfer Learning and data augmentation techniques to improve model accuracy. The system was developed to classify uniform neatness into two categories: neat and untidy. The test results show that the model is able to classify with an accuracy level of 73%, with precision, recall, and f1-score having the same results with an accuracy of 73%. These findings indicate that the developed system can help teachers and schools in evaluating student discipline objectively and continuously. Thus, this study contributes to improving the quality of education through the habituation of orderly behavior integrated with technology.

Keywords: Convolutional Neural Networks, Discipline, Image Classification, Scout Uniforms, Student Neatness.

Intisari— Kerapihan siswa dalam berpakaian Pramuka merupakan bentuk implementasi kedisiplinan yang mencerminkan kepatuhan terhadap aturan sekolah. Di SDIT Ajimutu Global Insani, atribut berpakaian yang dinilai meliputi kelengkapan baju Pramuka. Kerapihan dalam mengenakan atribut ini sangat menunjang terciptanya lingkungan belajar yang tertib dan kondusif. Penelitian ini bertujuan untuk mengklasifikasikan tingkat kerapihan berpakaian Pramuka secara otomatis menggunakan pendekatan berbasis kecerdasan buatan (Artificial Intelligence). Data yang digunakan berupa citra siswa yang direkam menggunakan kamera DSLR Canon EOS 60D, dengan jumlah total data sebanyak 510 gambar, terdiri dari 88 siswa perempuan dan 82 siswa laki-laki. Metode yang digunakan dalam penelitian ini adalah Convolutional Neural Network (CNN) dengan pendekatan transfer learning menggunakan arsitektur MobileNetV2 dengan Transfer Learning dan teknik augmentasi data untuk meningkatkan akurasi model. Sistem dikembangkan untuk mengklasifikasikan kerapihan seragam ke dalam dua kategori: rapi dan tidak rapi. Hasil pengujian menunjukkan bahwa model mampu melakukan klasifikasi dengan tingkat akurasi mencapai 73%, dengan presisi, recall, dan f1-score memiliki hasil yang sama dengan akurasi yaitu 73%. Temuan ini menunjukkan bahwa sistem yang dikembangkan dapat membantu guru dan pihak sekolah dalam melakukan evaluasi kedisiplinan siswa secara objektif dan berkelanjutan. Dengan demikian, penelitian ini memberikan kontribusi dalam meningkatkan kualitas pendidikan melalui pembiasaan perilaku tertib yang terintegrasi dengan teknologi.

Kata Kunci: Jaringan Saraf Tiruan Konvolusional, Disiplin, Klasifikasi Citra, Seragam Pramuka, Kerapihan Siswa.



INTRODUCTION

Student discipline is a crucial factor in creating a conducive learning environment. One aspect that reflects discipline is neatness in dressing, especially regarding the scout uniform. School uniforms reflect equality and discipline. Untidiness is not merely a violation of rules, but a form of identity expression within the framework of educational norms [1]. Wearing the uniform correctly and according to regulations not only demonstrates compliance with school regulations but also fosters habits of discipline that can have a positive impact on students' character development [2]. Although often considered trivial, neatness has deep meaning. Neatness reflects readiness to learn, respect for the school, and personal responsibility. A neat appearance shows students' compliance and readiness to undergo the learning process. Considering the varying levels of student neatness, an objective system is needed that can classify the level of clothing neatness with high accuracy so that the school can carry out effective evaluation and discipline monitoring.

Along with technological advances, artificial intelligence (AI)-based approaches are becoming increasingly popular. AI is a computer system capable of performing tasks that usually require human intelligence, where the process includes learning, reasoning, and self-correction [3]. AI is designed to evolve independently based on the input or information it receives, unlike regular programs that follow fixed instructions [4].

The design of artificial intelligence systems plays an important role in supporting education through the use of appropriate and efficient technology [5]. Convolutional Neural Network (CNN) is a machine learning technology with the potential to automate the classification of students' attire through image pattern recognition. CNN, as a deep learning method, has revolutionized automatic visual recognition and effectively solved the problem of object identification [6]. CNN methods have been widely used in various fields such as agriculture, medicine, and autonomous vehicles [7]. CNN is effective for coffee maturity classification—accurate, efficient, and applicable to other agricultural fields[8]. There is a study that applies the CNN method and obtains an accuracy value of 70.46%, a precision value of 71% and a recall value of 70%. [9]. The application of AI, especially CNN, has driven significant progress in image processing [10]. Clothing classification is still challenging due to the variety of styles and textures, but CNNs have proven to excel at handling this task [11].

The rapid progress of CNN and transfer learning opens up opportunities for increasing accuracy in image classification [12]. For the classification and prediction tasks, CNN is used. It helps in classifying the extracted features from the image frames[13]. Detecting student behavior in smart classes is an important focus to support the quality of learning [14]. Automating uniform inspection with AI is an effective solution, supported by an algorithm that is able to detect the suitability of student uniforms [15]. Deep learning-based object detection technology has made significant progress [16].

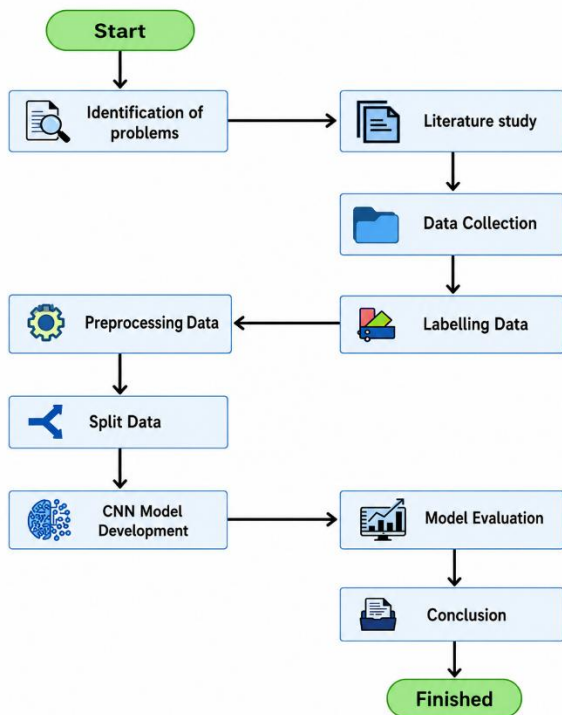
The integration of these computer vision-based monitoring systems allows teachers to obtain real-time feedback regarding interaction dynamics within the classroom [17]. Furthermore, the utilization of metadata from behavior classification results can be used to formulate more personalized pedagogical intervention strategies for each student [18]. The implementation of this technology is expected to not only improve discipline through automated inspection but also create a safer and more measurable learning environment through AI-based supervision [19].

This research aims to develop a neatness classification system for Scout uniforms based on recorded images processed using data augmentation and transfer learning techniques. This system automatically categorizes neatness into neat and untidy categories. Furthermore, this research is expected to assist teachers and schools in assessing student discipline more objectively and contribute to improving the quality of education by fostering orderly behavior within the school environment.

The use of CNN enables automatic and continuous classification of student neatness, while simultaneously supporting values-based, discipline-based, and humanitarian education. This system helps schools target students effectively through neatness data, fostering a culture of responsibility and self-care. Thus, technology not only accelerates evaluation but also strengthens character building within the educational environment.

MATERIALS AND METHODS

This research is quantitative with elements of a qualitative approach and uses an experimental design. The main focus of this study is to apply a Convolutional Neural Network (CNN) model to recognize and differentiate the neatness level of Scout uniforms through visual data in the form of images.



Source: (Research Results, 2025)
Figure 1 Research Flow Stages

The stages in this research are explained based on Figure 1 as follows:

1. Beginning: The initial stage in the research process.
2. Problem identification focused on the need for an automated system capable of objectively and efficiently assessing the neatness of student uniforms.
3. Literature Review: Reviewing supporting theories such as the foundations of CNN, MobileNetV2, image classification, and relevant previous studies.
4. Data Collection: Taking images of students in Scout uniforms directly in the field, with various shooting angles (front, left, right) and considering uniform attributes.
5. Data Labeling: The process of labeling images into two classes: Neat and Untidy, based on the visual attributes of the uniforms.
6. Data Preprocessing: Resizing images (e.g., to 224x224 pixels), normalizing pixel values, and performing data augmentation (such as rotation, flipping, zooming, and lighting adjustments) to enrich the data variety.
7. Splitting the Dataset: The dataset is divided into two parts:
 - a. 80% for training
 - b. 20% for validation
8. Developing a CNN Model: Using the MobileNetV2 architecture with a transfer

- learning approach, replacing the output layer to match the number of classes, and performing fine-tuning and hyperparameter adjustments.
9. The model is trained using the training data and evaluated using the validation data, using techniques such as early stopping to prevent overfitting.
10. Model Evaluation: The model is tested using the test data and then evaluated using metrics such as accuracy, precision, recall, F1-score, and confusion matrix.
11. Result Analysis: The evaluation results are analyzed to assess the model's effectiveness in classifying images of student uniform neatness.
12. Conclusions and Recommendations: Summarizes the research results and provides suggestions for future system improvements or development.
13. Finish: Marks the end of all research stages.

Each student was photographed from three different positions: front, right side, and left side, to give the model a more complete visual perspective. The distribution of data based on labels is as follows:

Table 1 Total Dataset

Label Category	Total data
Neat	255
Untidy	255
Total data	510

Source: (Research Results, 2025)

The images were taken in well-lit conditions, while taking into account the students' natural expressions to approximate real-life situations. The images were taken approximately 2 meters from the subject (the students). The following images are labeled:

Table 2 Labeling

No	Label	Number of attributes	Description
1	Neat	4-5	Complete attributes such as hat, scarf, badge
2	Untidy	0-3	Many missing or messy uniform components

Source: (Research Results, 2025)

Labels are determined based on the completeness of the main attributes of the Scout uniform. An image is labeled "neat" if all attributes are worn correctly, and "untidy" if there are any deficiencies. Labeling was done manually by separating the images into two folders: "neat" and "untidy." Data preprocessing was performed using Google Collaboratory (Colab), with the following steps:



1. Resize: All images were resized to 224x224 pixels to conform to the CNN model's input standards.
2. Normalization: Image pixel values were normalized to the [0, 1] range to improve model training stability.
3. Augmentation: Augmentation techniques were applied to artificially increase data diversity.

The preprocessed image results:



Source: (Research Results, 2025)
 Figure 2 Preprocessing Results

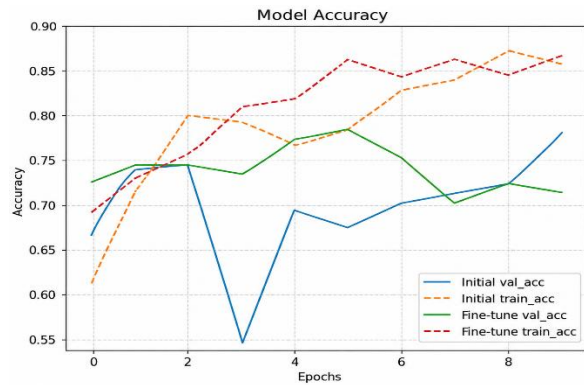
The dataset is then divided into two parts:

1. Training data (training set) – used to train model parameters
2. Validation data (validation set) – used to evaluate model performance during training and dynamically adjust parameters

RESULTS AND DISCUSSION

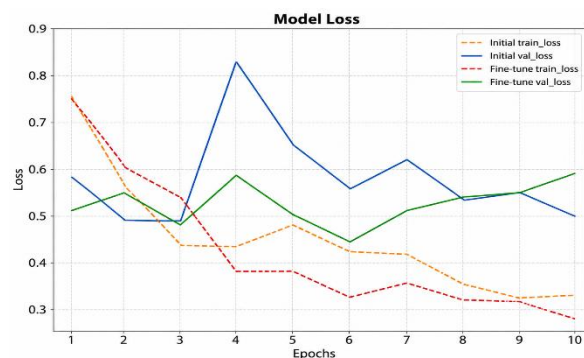
The accuracy graph in Figure 3 shows the development of model accuracy values against the training and validation data over 10 training epochs. The accuracy graph shows a trend of increasing model performance as the number of epochs increases.

Training accuracy can be seen to increase rapidly from around 0.60 to 0.80 in the first three epochs. However, validation accuracy tends to fluctuate and declines in the third epoch, reaching around 0.54. This indicates that the model is beginning to overfit, meaning it is overfitting to the training data, resulting in a decline in performance on the validation data.



Source: (Research Results, 2025)
 Figure 3 Accuracy Graph

After fine-tuning, model performance shows a more stable improvement. Training accuracy, indicated by the dashed red line, continues to increase to over 0.85, while validation accuracy, depicted by the green line, remains in a more consistent range, although there is a slight decline after reaching a peak in the fifth and sixth epochs. The best validation performance occurs in the fifth and sixth epochs, with an accuracy approaching 0.79, indicating that the model has learned more effectively and is able to generalize to previously unseen data. Thus, the fine-tuning stage successfully improves the overall model performance, both in terms of accuracy and training stability. Besides accuracy, the loss matrix is also an important indicator in evaluating model training performance.



Source: (Research Results, 2025)
 Figure 4 Loss Graph

Before fine-tuning, the training loss (shown by the dashed orange line) decreased consistently from around 0.75 to 0.4, indicating that the model was able to adapt to the training data. However, the validation loss (shown by the blue line) fluctuated significantly, particularly in the fourth epoch, where it spiked to nearly 0.85. This indicates that the model is experiencing overfitting, where performance on the training data continues to

improve but is not followed by the same performance on the validation data. After fine-tuning, the model's performance in reducing the loss value became more stable. The dashed red line shows the loss on the training data after fine-tuning, gradually decreasing until it reached a value below 0.3 in the final epoch. The accuracy metric shows the total proportion of correct predictions, while precision measures the extent to which the model's positive predictions are truly relevant (correct). Recall indicates the proportion of positive data the model correctly recognizes, and the F1-score is the harmonic mean of precision and recall.

Table 3 Accuracy Results

Matrix	Results
Accuracy	73%
Precision	73%
Recall	73%
F1-score	73%

Source: (Research Results, 2025)

The evaluation results table shows that the four main metrics used in this study—accuracy, precision, recall, and F1-score—have a consistent value of 73%. An accuracy value of 73% indicates that, of all the test data provided, 73% of the model's predictions matched the actual labels. A precision value of 73% means that of all predictions classified by the model as positive (both "neat" and "untidy"), 73% were correct. Recall was also at 73%, indicating that the model successfully recognized 73% of all data that were actually positive. Meanwhile, an F1-score of 73% also indicates a good balance between precision and recall, and indicates that no one metric dominates, leading to performance imbalances. Model performance evaluation for the "neat" class was conducted by measuring four main metrics: accuracy, precision, recall, and F1-score.

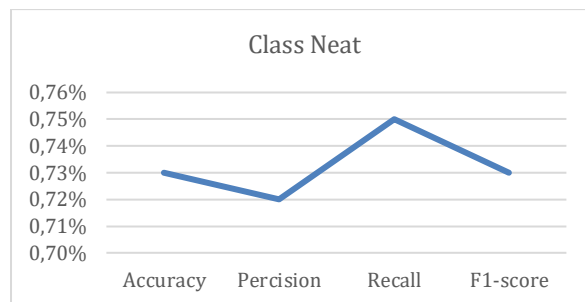
Table 4 Accuracy Results of Neat Class

Class Neat	
Accuracy	0.73
Precision	0.72
Recall	0.75
F1-Score	0.73

Source: (Research Results, 2025)

Based on the evaluation results, the model achieved an accuracy of 0.73 for the "neat" class, meaning 73% of all model predictions for this class matched the actual label. Precision for this class was 0.72, indicating that 72% of all model predictions for "neat" were accurate. Meanwhile, recall was the highest at 0.75, meaning the model was able to recognize 75% of all "neat" images as true. The F1-

score obtained was 0.73, indicating a balance between precision and recall for this class.



Source: (Research Results, 2025)

Figure 5 Neat Class Graph

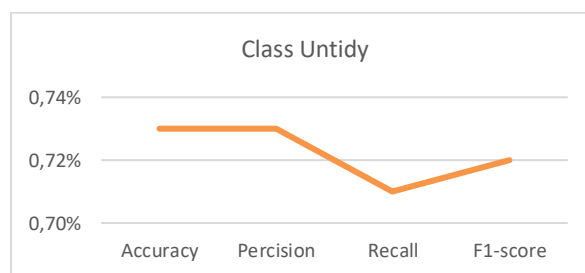
The neat class graph reinforces the understanding of model performance in the "neat" class, where the recall value is highest compared to the other metrics. This graph helps illustrate how each metric contributes to the model's performance evaluation for a specific class. Model performance evaluation for the "untidy" class was conducted by measuring four main metrics: accuracy, precision, recall, and F1-score.

Table 5 Accuracy Results for the Untidy Class

Classroom is Not Tidy	
Accuracy	0.73
Precision	0.73
Recall	0.71
F1-Score	0.72

Source: (Research Results, 2025)

Based on the evaluation results, the model accuracy for this class was 0.73, meaning 73% of the total predictions for the "untidy" class matched the actual label. Precision was also at 0.73, indicating that of all the model predictions stating "untidy," 73% were actually correct. On the other hand, recall for this class was slightly lower, at 0.71, indicating that of all the actual "untidy" images, only 71% were successfully recognized by the model. The F1-score of 0.72 reflects a balance between precision and recall, although slightly leaning towards precision.

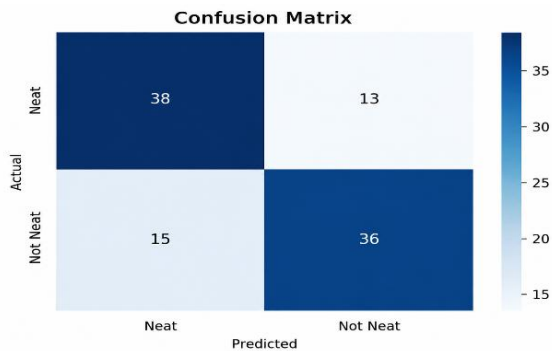


Source: (Research Results, 2025)

Figure 6 Untidy Class Graph



Figure 6 shows that the model has high and stable precision, but lower recall compared to the "tidy" class. This indicates that the model is more cautious in classifying images as "untidy," which may result in some "untidy" images being missed optimally (false negatives). The model's performance in the "untidy" class can be categorized as good and balanced, but there is still room for improvement, particularly in increasing recall so that the model can correctly recognize more "untidy" cases. The confusion matrix displays the number of correct and incorrect predictions for each class, making it easier to identify the types of errors (false positives and false negatives) that are still occurring in the model.



Source: (Research Results, 2025)
Figure 7 Confusion Matrix Results

The confusion matrix in Figure 7 shows the model's performance in classifying test data based on the actual labels and predicted results. This matrix provides a more detailed overview of the types of errors made by the model. Of the 51 images labeled "neat," 38 were correctly classified, while 13 were misclassified as "untidy." Meanwhile, of the 51 images labeled "untidy," 36 were correctly recognized, and 15 were misclassified as "neat." These results indicate that the model has fairly balanced classification ability between the two classes. Although there were still errors, such as 13 false negatives in the "neat" class and 15 false positives in the "untidy" class, the *error distribution was relatively even*.

Two examples of prediction results are shown in Figures 6 and 7. These images were obtained from Google search results to test the model's generalization ability on data not included in the training set. This evaluation is important to determine how the model performs when faced with data from outside its original domain. Class labels are determined based on the alphabetical order of folder names. Because the "neat" folder appears before "untidy," the system automatically assigns a label of 0 to the "neat" class and a label of

1 to the "untidy" class. Therefore, a prediction value close to 0 indicates a model bias toward the "neat" class, while a prediction value close to 1 indicates a bias toward the "untidy" class.



Source: (Research Results, 2025)
Figure 8 Neat Classification Prediction Results

In Figure 8, the model predicts this image with a 0.21 confidence level. With a 0 for the "neat" class, a 0.21 confidence level indicates that the model is fairly confident that this image falls into the "neat" category. While this number may seem low, in the context of the binary labeling used, it actually indicates a 79% confidence level in the "neat" class.



Source: (Research Results, 2025)
Figure 9 Untidy Classification Prediction Results

The model provided a prediction score of 0.94 for images classified as "untidy" from Figure 9 (from <https://sma3jogja.sch.id/seragam/>). This prediction score also reflects a 94% probability that the image belongs to the "untidy" class. The results showed that the CNN model with the MobileNetV2 architecture, developed using a transfer learning and fine-tuning approach, performed reasonably well in classifying images of students' tidiness. Based on the initial training and fine-tuning results, model accuracy increased, particularly on the training data, reaching over 85%, and validation accuracy remained relatively stable at 72–79%.

This indicates that the fine-tuning process successfully improved the model's generalization ability without causing significant overfitting. Model performance evaluation using accuracy, precision, recall, and F1-score metrics provides a balanced picture of both classes, namely "neat" and "untidy." Overall, the model achieved an accuracy of 73%, with precision, recall, and F1-score also at similar figures. Evaluation per class shows that the model is slightly better at recognizing the "neat" class (recall 0.75) than the "untidy" class (recall 0.71), although the difference is not significant. This indicates that the model has a fairly high sensitivity in detecting images of students with a neat appearance, but still needs to be improved in its ability to detect irregularities.

The confusion matrix strengthens the evaluation results by demonstrating a fairly balanced classification distribution. Of the 102 test images, the model successfully classified 74 correctly and made 28 errors, fairly evenly distributed between the two classes. The number of false negatives and false positives did not show a dominant bias toward any particular class, indicating that the model was fair and consistent in its classification. Overall, the results obtained from this study demonstrate that the combination of the MobileNetV2 architecture with transfer learning and fine-tuning can be used effectively for image-based student neatness classification tasks.

CONCLUSION

Based on the training and evaluation results, the model was able to classify with an accuracy of 73%, as well as consistent precision, recall, and F1-score values of 73%. The evaluation per class also showed balanced results, with the highest recall in the "neat" class at 0.75 and in the "untidy" class at 0.71. Analysis of accuracy and loss graphs during training indicates that the fine-tuning process successfully improved model performance, reduced overfitting, and produced better generalization to the test data. Test results on new images from outside the dataset (obtained from the internet) show that the model is able to classify images quite well, based on predicted values that match the labeling scheme used, namely the "neat" class is labeled 0 and "untidy" is labeled 1. Prediction values close to 0 or 1 indicate the level of confidence of the model in one of the classes. However, the level of confidence of the model in a prediction is still influenced by various visual factors, such as body pose, additional attributes on the uniform, background, and the number of individuals in one image. This indicates that the model has a fairly

good generalization ability to data outside the training, but remains sensitive to significant visual variations. Thus, the classification system developed in this study has been proven to be able to help schools in evaluating student neatness objectively, efficiently, and sustainably, and has the potential to be further developed to support the development of disciplinary character in the educational environment.

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