Journal of Artificial Intelligence and Engineering Applications

Website: https://ioinformatic.org/

15th October 2025. Vol. 5. No. 1; e-ISSN: 2808-4519

Image Restoration and Helmet Usage Violation Detection using the Lucy-Richardson Deconvolution Algorithm and Convolutional Neural Network (CNN) Method

M.Redo anugroho[1]*, Lastri Widya Astuti [2], Indah Permatasari [3]

[1,2,3]*Universitas Indo Global Mandiri*
202110008@studenst.uigm.ac.id[1], lastriwidya@uigm.ac.id[2], Indah@uigm.ac.id[3]*

Abstract

The high number of traffic violators on the road due to motorcyclists not wearing helmets remains a serious problem, despite the implementation of the electronic ticketing system (ETLE). One of the challenges in detecting these violations is the poor image quality caused by blurring. This study proposes a combined method using the Lucy-Richardson Deconvolution restoration algorithm and classification using a Convolutional Neural Network (CNN) to improve the accuracy of violation detection. The dataset used consists of 1,101 images extracted from videos, divided into two classes: wearing a helmet and not wearing a helmet. The images were tested with and without the restoration process to compare detection performance. After undergoing restoration and CNN model training, the system achieved an accuracy of 93% on the test data. The detection results showed a significant improvement compared to images without restoration, where accuracy only reached 87%. In addition, the system can process blurred images and classify helmet objects more accurately based on evaluation using a confusion matrix and bounding box visualisation. Thus, the integration of the Lucy-Richardson Deconvolution algorithm with CNN has proven to be effective in improving image quality and helmet violation detection accuracy, and has the potential to be applied to ETLE systems to support automated traffic law enforcement.

Keywords: *Restorasi Citra, Lucy-Richardson Deconvolution, CNN, Deteksi Helm, Klasifikasi Citra, ETLE*

1. Introduction

Traffic accidents in Indonesia remain a serious problem, especially among motorcyclists who do not wear helmets. Helmets play an important role in protecting the head and can reduce the risk of serious or fatal injuries in the event of an accident [1]. Based on data from South Sumatra Province, in 2022 there were 1,923 traffic accidents recorded [2]. Although the electronic ticketing system has been implemented, violations such as not wearing a helmet are still common, contributing to high accident rates and fatalities. As an effort to improve traffic safety, the Indonesian government has implemented Electronic Traffic Law Enforcement (ETLE) or electronic ticketing, including in the city of Palembang since 2021. The implementation of ETLE is regulated in Article 272 of Law Number 22 of 2009 concerning Road Traffic and Transportation [3]. One of its main uses is to spot motorcyclists not wearing helmets by analysing moving images. But sometimes the images are blurry, making it hard to spot the offenders [4].

Advances in computer vision technology enable systems to recognise and understand images or videos in the same way as human vision [5]. Several studies have been conducted on helmet detection using Convolutional Neural Network (CNN) and You Only Look Once (YOLO) algorithms [6]. [7] report accuracy 89,04%, [8] achieve 84,6%, whereas [9] obtain 70,49%. The results show that the accuracy rate is greatly influenced by image quality. Research by [10] proving that the Lucy-Richardson Deconvolution method is capable of restoring blurred images by up to 50% with a minimum PSNR value of 30 dB. Based on these conditions, this study aims to integrate Lucy-Richardson Deconvolution for image restoration and the CNN method in [11] detecting helmet violations among motorcyclists. It is hoped that this approach can improve the accuracy of detection in electronic ticketing systems, particularly in the city of Palembang, and contribute to the development of deep learning-based traffic law enforcement technology.

2. Research Method

This research was conducted through several systematic stages to improve the accuracy of detecting helmet violations among motorcyclists [12]. The initial stage began with problem identification and literature review to understand image restoration and object detection methods. Data was obtained from video recordings of motorcyclists around the University of Muhammadiyah Palembang Pedestrian Bridge under clear conditions, then converted into .jpg images and cropped to a resolution of 130×130 pixels. The collected images were grouped into two categories riders wearing helmets and those not wearing helmets. Next, image restoration was performed using the Lucy-Richardson Deconvolution algorithm to reduce the blur effect. After restoration, the images were divided into training data and test data for model training. The detection process was performed using a CNN architecture [13] YOLO-based model trained with restored training data. The trained model was then tested using test data to evaluate the system's accuracy in identifying violations. The entire process and analysis results were archived as a basis for evaluating the effectiveness of the proposed method.

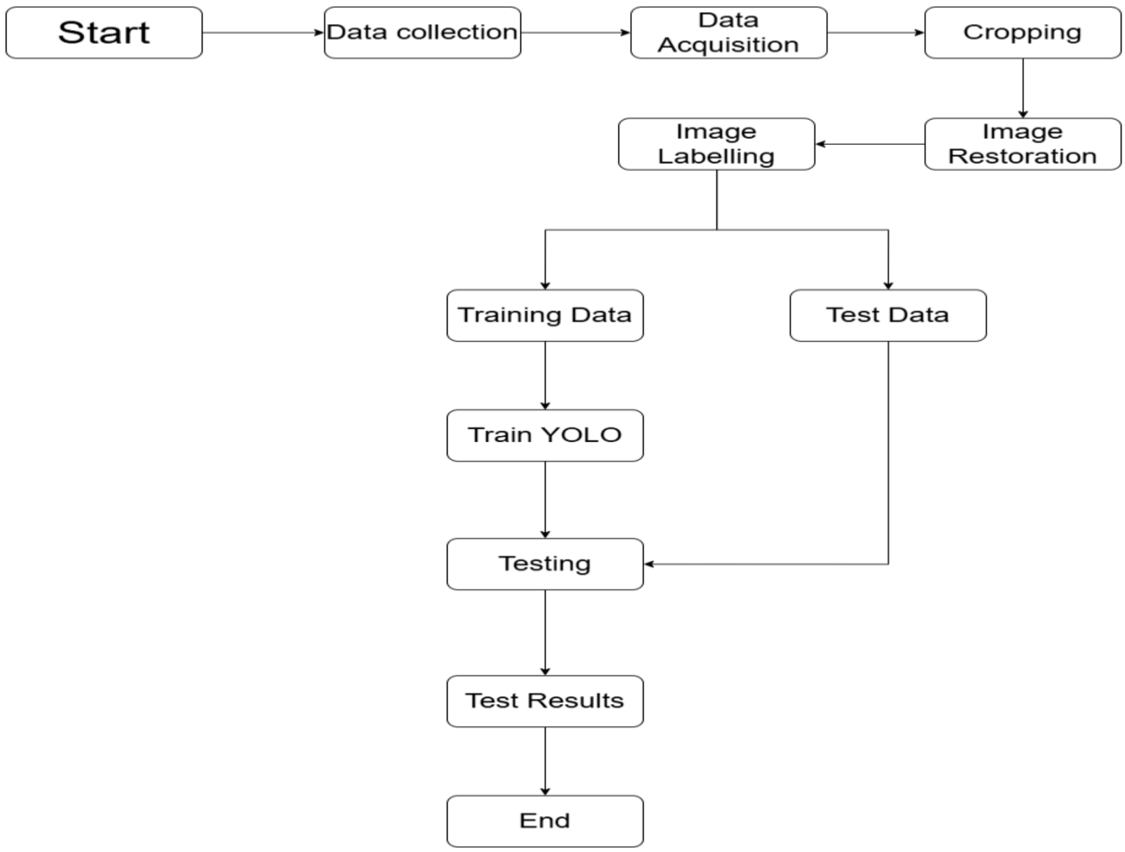

Fig. 1: Research Framework

2.1. Data Collection

Data was collected through direct observation and documentation at the University of Muhammadiyah Palembang Pedestrian Bridge (JPO), located on Jl. Jenderal Ahmad Yani, Palembang City. Observations were made from above the JPO to record traffic activity, particularly the behaviour of motorcyclists in relation to helmet use. The data collection process involved recording videos using a 720p resolution mobile phone camera for 20 minutes per video, with a total of three videos under clear weather conditions. The recording position was focused on the front view of the riders to obtain relevant images for classifying helmet users and non-helmet users. The dataset from these recordings was used in the restoration and violation detection process, consisting of 1,101 images.

2.2. Data Acquisition

At this stage, data acquisition was carried out after successfully collecting video recordings containing the activities of motorcyclists, both those wearing helmets and those not wearing helmets. The video recordings were 20 minutes long with a resolution of 720p. Next, the video is converted into a collection of .jpg images using VLC Media Player software, which has a built-in feature for converting video into images. The conversion process is carried out by taking one frame every 10 seconds.

2.3. Cropping

The image cropping stage is part of the data selection and management process, in which irrelevant objects such as cars, buses, and pedicabs are filtered out. This is done in order to focus attention only on motorcyclists who wear helmets and those who do not. At this stage, the converted image is cropped and resized to 130 x 130 pixels using Microsoft Office Picture Manager. This software is used to simplify the resizing process and focus on the desired object area.

2.4. Image Restoration

After cropping, the image is restored using the Lucy-Richardson Deconvolution algorithm implemented in MATLAB software. This process is intended to improve the sharpness of blurred images, whether from riders wearing helmets or not. Restoration is performed iteratively using the Point Spread Function (PSF) as a light diffusion model. The PSF used is adjusted to the characteristics of the blur, such as Gaussian for defocus or motion blur. Each iteration involves convolution between the image estimate and the PSF, and the result is compared with the blurred image to gradually correct the estimate. The iteration continues until the image quality reaches the desired convergence. The restored image is then used as training data and test data in the classification stage.

$$h\,(x,y), yaitu\ g(x,y) \;=\; (f * h)\,(x,y) \;+\; n(x,y) \qquad (1)$$

- $g(x, y)$: blurry image (observation result).
- $f(x, y)$: the original image to be restored.
- $h(x, y)$: PSF function, which models the propagation of light.
- $n(x, y)$: noise (digital usually assumed to be Poisson noise for digital images).

2.5. Image Labelling

The labelling process is carried out to classify images into two categories, namely riders who wear helmets and those who do not. This process uses Roboflow software, where each image is annotated manually by providing a bounding box on the rider's head area. Labelling is done consistently so that the system can accurately distinguish classes when training the model. Inconsistencies in naming, such as differences in letter or symbol spelling, can disrupt model performance. The labelled dataset is then saved and exported in a suitable format, such as YOLO, for model training purposes in the next stage.

2.6. Test Data

CNN model [13] trained using the YOLO framework with the Hold-Out method, where 80% of the total 881 images were used as training data. Each image has been given a bounding box and label for two classes, namely riders wearing helmets and those not wearing helmets. The training process aims to enable the model to accurately recognise objects in detecting helmet violations among motorcyclists.

2.7. Training Data

A total of 20% of the 220 images were used as test data to evaluate the generalisation ability of the CNN model in detecting motorcyclists wearing helmets and those not wearing helmets. The Hold-Out method was used in data division, with images selected randomly while still considering the diversity and relevance of objects. This stage aims to measure the accuracy and reliability of the model against new data that was not used during training. It is capable of accurately recognising objects in detecting helmet use violations among motorcyclists.

3. Results and Discussion

3.1. Restoration Results Using the Lucy-Richardson Deconvolution Algorithm

In this restoration process stage, the Lucy-Richardson Deconvolution Algorithm is used on several input data that will be used as input data for the classification process. The application of the Lucy-Richardson Deconvolution Algorithm aims to determine whether the blurred image data can be improved into a better image or whether it will become worse.

before restoration After restoration

Fig. 2: Restoration Results

The restoration of blurred images yielded satisfactory results, but at first glance there appeared to be no significant difference between the unrestored and restored images. Next, MSE and PSNR values were calculated to evaluate whether the restored images had undergone any change in quality compared to the original images. Through these values, the effectiveness of the restoration process that has been applied can be determined. The complete MSE and PSNR calculation results are presented in Table 1.

Table 1: MSE and PSNR values

Wearing a Helmet		
No	MSE	PSNR
1	0.0001	39.77
2	0.0001	40.15
3	0.0002	37.15
Not Wearing a Helmet		
No	MSE	PSNR
1	0.0001	38.69
2	0.0001	39.35
3	0.0002	38.00

3.2. Traininng Results

The CNN model was implemented using the YOLO framework and trained online through the Google Colab platform. Training was conducted with varying numbers of epochs (20 to 100) to determine the most optimal configuration for detecting motorcyclists who wear and do not wear helmets. Model performance evaluation was conducted by measuring the Precision, Recall, and mean Average Precision (mAP) metrics, including mAP@50 and mAP@50–95. The use of these metrics aims to assess the detection accuracy and effectiveness of the model at various threshold levels (IoU threshold). The results of the entire training for each model are shown in Table 2.

Table 2: Model training results using varying numbers of epochs

No	Precision	Recall	mAP@50	mAP@50-90
20	0.881	0.854	0.933	0.561
30	0.846	0.904	0.925	0.578
40	0.855	0.891	0.938	0.581
50	0.823	0.833	0.912	0.585
60	0.817	0.837	0.926	0.574
70	0.897	0.855	0.950	0.581
80	**0.912**	**0.884**	**0.940**	**0.582**
90	0.847	0.853	0.925	0.575
100	0.870	0.892	0.935	0.580

3.3. Analysis of Training Results

Based on the training results, the model performance showed variation at each epoch. The highest precision value was obtained at epoch 80, which was 0.912, but it decreased at epochs 90 and 100, indicating the possibility of overfitting. Meanwhile, the highest recall value was achieved at epoch 100, at 0.892, although at epoch 80 the value was slightly lower at 0.884. This indicates a trade-off between precision and recall at each epoch. For the mAP metric, the mAP@50 value at epoch 80 was 0.94, while mAP@50–95 achieved the highest performance, at 0.582. Although mAP@50 is not maximal, the optimal combination of precision and mAP@50–95 indicates that epoch 80 is the best point in training the YOLO model to detect helmet violations, balancing accuracy and generalisation.

3.4. Model testing

After the training process is complete, the next stage is to test the model to evaluate its ability to detect and classify motorcyclists who wear helmets and those who do not. The test data used consists of blurred images and restored images, each comprising 220 images, with a balanced distribution across two classes: 110 images for riders wearing helmets and 110 images for those not wearing helmets. All of this test data was not used in the previous training process, thereby representing the model's generalisation performance on new data. The detailed distribution of test data for each class is presented in Tables 3 and 4.

Table 3: Amount of restoration image test data

Object Class	Amount
Wear a helmet	110
Not Wearing a Helmet	110
Total	220

Table 4: Amount of blur image test data

Object Class	Amount
Wear a helmet	110
Not Wearing a Helmet	110
Total	220

3.5. Model testing results

Model testing was conducted using the model results obtained from the previous training process, namely at epoch 80, which was selected because it showed optimal performance based on the evaluation metrics on the training data. At this stage, the trained object detection model was used to identify motorcyclists wearing helmets and not wearing helmets in the test data. The results of the model testing in detecting motorcyclists wearing helmets and not wearing helmets can be seen in Table 5, which displays the Confidence Score or confidence level in recognising the detected objects, and also in Figure 3, which shows the output results of the detection of motorcyclists wearing helmets and not wearing helmets.

Table 5: Confidance Score

No	Object Class	*Confidance Score*
1	Wear a helmet	0.80
2	Wear a helmet	0.86
4	Not Wearing a Helmet	0.79
5	Not Wearing a Helmet	0.72

Fig. 3: Object detection output results

From a total of 220 images in each test data set, both blurred and restored, model testing was conducted to measure detection performance. At this stage, the number of correct and incorrect predictions for each object class was calculated, namely motorcyclists wearing helmets and those not wearing helmets. A summary of the prediction results obtained from the model testing is presented in Tables 6 and 7.

Table 6: Restoration image prediction results

Object Class	Correct Prediction (TP)	Wrong Prediction (TN)
Wear a helmet	98	12
Not Wearing a Helmet	109	1
Total	207	13

$$accuracy = \frac{98 + 109}{110 + 110} = \frac{207}{220} \times 100\% = 94.09\%$$

Table 7: blurred image prediction results

Object Class	Correct Prediction (TP)	Wrong Prediction (TN)
Wear a helmet	72	38
Not Wearing a Helmet	108	2
Total	180	40

$$accuracy = \frac{72 + 108}{110 + 110} = \frac{180}{220} \times 100\% = 81.82\%$$

3.6. Discussion

Image restoration using the Lucy-Richardson Deconvolution algorithm shows an improvement in the visual quality of blurred images. Although the difference is not very noticeable visually, quantitative evaluation using PSNR values shows that most of the restored images have values above 38 dB, indicating a high degree of similarity to the original image (see Table 1). The CNN model implemented through the YOLO framework was trained on the Google Colab platform with an exploration of the number of epochs between 20 and 100. Evaluation was performed using the metrics precision, recall, mAP@50, and mAP@50–95. The best results were achieved at epoch 80, with a precision of 0.912 and mAP@50–95 of 0.582. The decrease in recall at higher epochs indicates overfitting, where the model becomes overly adjusted to the training data. During the testing phase, the model trained at epoch 80 achieved an accuracy of 94.09% on the restored image data (207 correct predictions out of 220) and 81.82% on the blurred image data (180 correct predictions out of 220). The confidence scores of the predictions are generally above 0.50, with the highest score reaching 0.90. However, some classification errors occur in images with low confidence scores (≤ 0.50), even as low as 0.00. This is likely due to differences in visual characteristics between the test data and the training data, such as background or object perspective.

4. Conclusion

This study shows that the use of the Lucy-Richardson Deconvolution algorithm can significantly improve image quality. Testing using a confusion matrix yielded an accuracy of 94.09% on restored images, compared to 81.82% on blurred images. This proves that image restoration plays an important role in improving classification performance. The applied CNN model also demonstrated high performance in detecting helmet violations, making this combination of methods effective in supporting automatic violation detection systems.

5. Advice

Based on the results of the research that has been conducted, here are some suggestions that can be used as input for future researchers:
1. Add more object classes, such as excess passengers on motor vehicles, not using rear-view mirrors, and not using vehicle number plates.
2. Use video recording quality higher than 720p or use different camera devices.
3. Try collecting research data in rainy weather or at night.

References

[1] M. Dwi, O. S. Matompo, and I. Lestiawati, "Penerapan Sanksi Denda Terhadap Pengendara Motor Yang Tidak Menggunakan Helm (Studi Pada Kepolisian Resort Sigi)," *J. Sasi*, vol. 16, no. 22, pp. 1903–1917, 2019.
[2] SIMATA, "Satu Data Provinsi Sumatera Selatan," *Sist. Inf. Satu Data Sumsel*, no. 1, p. 34, 2021.
[3] S. Aprita and M. Nurlani, "Penegakan Hukum Lalu Lintas Melalui E-Tilang Dalam Meningkatkan Kesadaran Hukum Berlalu Lintas Di Kota Lubuk Linggau," *Karya J. Pengabdi. Masy.*, vol. 1, no. 2, pp. 54–64, 2024, doi: 10.70656/jpkm.v1i2.174.
[4] M. Cahyanti, M. Ridwan, and D. Septian, "A Real-Time Helmet Detection System Based on YOLOv8 to Support Traffic Law Enforcement Sistem Deteksi Penggunaan Helm Secara Real-Time Berbasis YOLOv8 untuk Mendukung Penegakan Hukum Lalu Lintas," vol. 29, no. 1, pp. 1–10, 2025, doi: 10.46984/sebatik.v29i1.2585.
[5] R. Gustriansyah, J. Alie, A. Sanmorino, R. Heriansyah, and M. N. Megat Mohamed Noor, "Machine Learning for Clustering Regencies-Cities Based on Inflation and Poverty Rates in Indonesia," *Indones. J. Inf. Syst.*, vol. 5, no. 1, pp. 64–73, 2022, doi: 10.24002/ijis.v5i1.5682.
[6] Z. R. Mair and M. A. Rahmanda, "Perbandingan Versi Terbaik YOLO Dalam Mendeteksi Jarak Spasi Antar Baris Tulisan Tangan," *J. Sains, Nalar, dan Apl. Teknol. Inf.*, vol. 4, no. 2, pp. 103–110, 2025, doi: 10.20885/snati.v4.i2.40414.
[7] K. Khoiriyah and M. F. A. A. Armawan, "Deteksi Pengendara Motor Tanpa Menggunakan Helm Dengan Algoritma Deep Learning Yolo," *Jeis J. Elektro Dan Inform. Swadharma*, vol. 3, no. 2, pp. 72–82, 2023, doi: 10.56486/jeis.vol3no2.360.
[8] S. B. Setyawan, W. Pribadi, H. Arrosida, and E. P. Nugroho, "Sistem Deteksi Pengendara Sepeda Motor Tanpa Helm dan Kelebihan Penumpang pada Dengan Menggunakan YOLO V3," *Semin. Nas. Terap. Ris. Inov.*, vol. 7, no. 1, pp. 430–438, 2021.
[9] Albert, K. Gunadi, and E. Setyati, "Deteksi Helm pada Pengguna Sepeda Motor dengan Metode Convolutional Neural Network," *J. Infra*, vol. 8, no. 1, pp. 295–301, 2020.
[10] M. Harahap, J. P. Sihombing, and A. R. Lubis, "Deblurring Citra Dengan Metode Lucy Richardson Deconvolution," vol. 3, no. April, pp. 441–454, 2020.
[11] Nurohman, Rudi Heriansyah, Dwi Asa Verano, and Zaid Romegar Mair, "Deteksi Penyakit Diabetes Retinopathy Menggunakan Citra Digital Dengan Metode Convolutional Neural Network (Cnn)," *Pros. Snast*, no. November, pp. 311–320, 2024, doi: 10.34151/prosidingsnast.v1i1.5120.
[12] "Kustoyo_2018110072.pdf-1.pdf."
[13] Pratama M. Duta, Gustriansyah Rendra, and Purnamasari Evi, "Klasifikasi Penyakit Daun Pisang Menggunakan Convolutional Neural Network (CNN)," *J. Teknol. Terpadu*, vol. 10, no. 1, pp. 1–6, 2024.