Combination of HAAR, HOG, and LBP Descriptors for Enhanced Classification of Moving Objects and Motorcyclists Wearing Helmets

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ABSTRACT

Many traffic accidents result in human casualties in many countries, especially for motorcyclists who do not wear protective helmets during the accident. In several regions, riding a motorcycle without a helmet is a legal offense. Reducing the number of helmetless motorcyclists can significantly save lives. Therefore, the development of an automated, real-time detection system can assist law enforcement in enforcing helmet use more effectively. Such a system demands high accuracy in identifying moving objects on highways and distinguishing between motorcyclists with and without helmets. This study employed feature extraction techniques, including HAAR, Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP), which were concatenated to enhance classification performance. HAAR features capture contrast differences in rider images, HOG detects the shape of the rider's head, and LBP analyzes the head texture. In addition, in this research, three classifiers were evaluated: Backpropagation Neural Network (BNN), Support Vector Machines (SVM), and Random Forest (RF). The results, based on a dataset of 1,956 images, demonstrated that the proposed concatenated descriptor achieved 99.75% accuracy in moving object classification using RF, and 96.75% accuracy in helmet detection using SVM and BNN. The method outperformed systems utilizing single or dual descriptors, indicating the effectiveness of the combined approach.

Keywords-combination; HAAR; Histogram of Oriented Gradients (HOG); Local Binary Patterns (LBP); moving object classification; helmet-wearing motorcyclist classification

I. INTRODUCTION

A significant proportion of traffic accident fatalities involve motorcyclists who do not wear helmets [1]. One effective way to reduce these deaths is through the strict enforcement of helmet laws. Although such laws exist in many countries, a considerable number of motorcyclists still fail to comply. Offenders can be automatically detected using Closed-Circuit Television (CCTV) systems, which are already installed in many urban areas.

Several studies have explored computer vision-based approaches for detecting helmet violations, primarily using different versions of the You Only Look Once (YOLO) object detection algorithm. Authors in [2] applied YOLOv3, while authors in [3] used YOLOv5, and authors in [4] implemented YOLOv8, which showed robustness to lighting variations. In [5], YOLOv8 was combined with morphological operations, and in [6], it was integrated with the Dark Channel Prior (DCP) method to enable detection under various weather conditions. Other researchers utilized descriptors for the feature extraction process. Authors in [7] deployed HAAR features and machine learning techniques, while authors in [8] combined HAAR with the Circular Hough Transform (CHT). Authors in [9–12] applied HOG for feature extraction, with promising results.

To further enhance performance, some researchers combined multiple descriptors. For example, authors in [13] combined Histogram of Oriented Phase (HOP), HOG, and Local Difference Binary (LDB), while authors in [14] fused LBP, color histograms, and Hu moment invariants. These combinations demonstrated better accuracy than using a single or dual descriptor. Other studies have applied descriptor fusion to different applications, such as palm recognition using HOG and Discrete Cosine Transform (DCT) [15], and object tracking using a combination of Convolutional Neural Network (CNN), HOG, and wavelet transforms [16].

The present study proposes a new combination of three descriptors—HAAR, HOG, and LBP—to improve helmet detection accuracy. HAAR features capture contrast variations, HOG extracts the structural shape of the motorcyclist's head, and LBP analyzes texture details. These complementary descriptors are expected to enhance detection performance. Furthermore, the study compares three machine learning classifiers: BNN, SVM, and RF. The combination that yields the highest accuracy and optimal computation time will be selected for practical implementation in real-time helmet violation detection systems.

II. MATERIALS AND METHODS

A. Dataset

Three subdatasets were used in this study: DS_moving_object, DS_motorcycle, and DS_motocyclist_head. These datasets were obtained from video recordings captured by a camera mounted on the upper edge of a highway in Semarang, Indonesia. The recordings were conducted in the morning under bright lighting conditions.

- DS_moving_object contains 1,956 images, including 800 images of motorcycles and 1,156 of non-motorcycle objects.
- DS_motorcyle includes the previous 800 images, evenly split between 400 motorcyclists wearing helmets and 400 not wearing helmets.
- DS_motocyclist_head consists of 800 cropped head images—400 of helmeted riders and 400 of non-helmeted riders—extracted from the DS_motorcycle dataset.

An example of a video frame from this recording is shown in Figure 1. Sample images from the DS_moving_object, DS_motorcycle, and DS_motorcyclist_head are displayed in Figures 2, 3, and 4, respectively.

Fig. 1. Example of a video frame recording.

Fig. 2. Examples of the DS_moving_object dataset.

Fig. 3. Examples of the DS_motorcycle dataset.

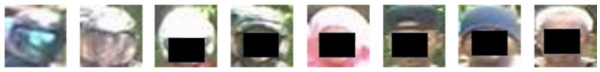

Fig. 4. Examples of the DS_motorcyclist_head dataset.

B. Proposed Method

The research on detecting motorcyclists not wearing helmets consists of several parts, which aim at the classification of moving objects and motorcyclists as helmet wearers or not. The proposed system is depicted in Figure 5.

1) Preprocessing (Resizing)

The first preprocessing step is resizing, where image dimensions in the DS_moving_object and DS_motorcycle datasets are reduced to 24×40 pixels. For the DS_motorcyclist_head dataset, the images are resized to a fixed dimension of 32×32 pixels. This resizing process is intended to accelerate both feature extraction and classification, reducing computational complexity without significantly compromising image quality.

2) Feature Extraction

The feature extraction process in this study combines three descriptors: HAAR, HOG, and LBP (HAAR + HOG + LBP). HAAR captures contrast differences in the image of a motorcyclist [17], HOG identifies the shape of the motorcyclist's head, and LBP analyzes its texture [18].

HAAR refers both to the Haar Wavelet, commonly used in signal and image analysis, and to Haar-like features, which are widely applied in object detection through the analysis of intensity differences across image regions. Authors in [19] utilized several HAAR filters to detect vehicles in static images, while authors in [20] introduced image integrals that can speed up calculations on the image subregion. In this study, four types of HAAR filters are employed: a two-rectangle horizontal feature (2×2), a two-rectangle vertical feature (2×2), a three-rectangle horizontal feature (2×2×2), and a three-rectangle vertical feature (2×2×2). Illustrations of each filter are presented in Figure 6.

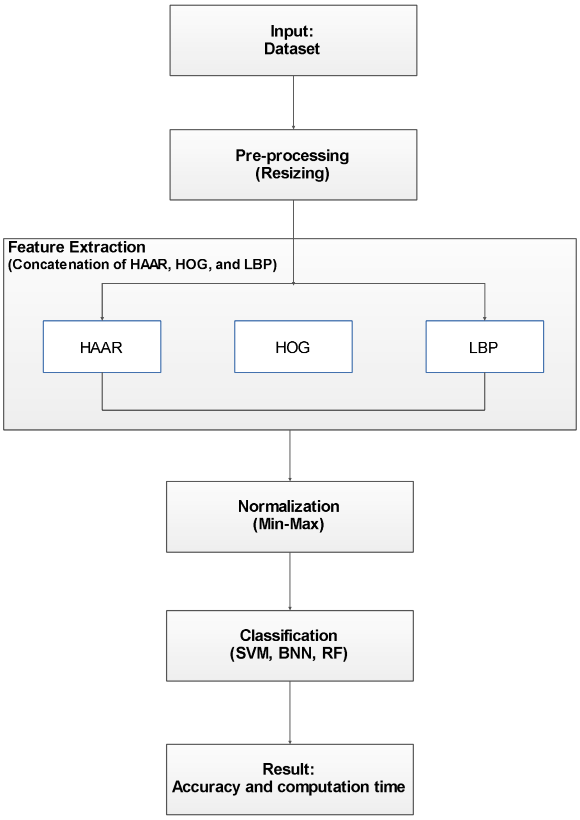

Fig. 5. Proposed system for classification of moving objects on the road and classification of motorcyclists wearing helmets.

HOG was introduced in [21] for human detection. The initial step in the descriptor process involves computing the horizontal gradient I_x and vertical gradient I_y, as exhibited in (1) and (2), respectively. I_m denotes the grayscale image, while D_x and D_y represent the masks [-1 0 1] and $[-1\ 0\ 1]^T$, respectively. The subsequent step involves computing the gradient magnitude $|Gr|$ and gradient orientation θ, as outlined in (3) and (4). HOG is implemented on an image segmented into multiple blocks, with each of them being further divided into cells. This study's HOG parameters include a cell size of 8×8, a block size of 2×2, and 9 bins for the orientation histogram.

$$I_x = I_m \times D_x \quad (1)$$

$$I_y = I_m \times D_y \quad (2)$$

$$|G_r| = \sqrt{I_x^2 + I_y^2} \quad (3)$$

$$\theta = tan^{-1}\left(\frac{I_y}{I_x}\right) \quad (4)$$

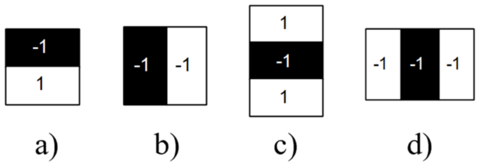

Fig. 6. HAAR filter utilized in this study: (a) horizontal feature with two rectangles, (b) vertical feature with two rectangles, (c) horizontal feature with three rectangles, and (d) vertical feature with three rectangles.

The original LBP operator evaluates eight neighbouring pixels using the average value as a threshold [22]. In this study, LBP is configured with 8 sampling points, a radius of 1, and an upright rotation setting. An illustration of the LBP calculation is provided in Figure 7.

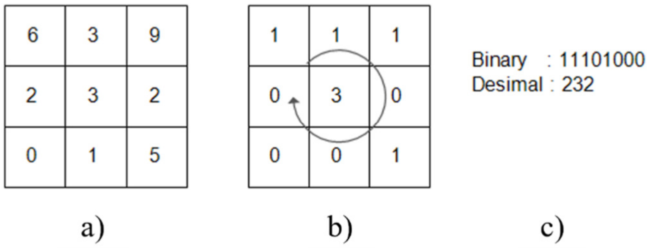

Fig. 7. Example of LBP calculation: (a) window, (b) threshold, and (c) pattern computed.

3) Normalization

The normalization technique employed in this study is Min-Max normalization, which scales the feature extraction output to a range between 0 and 1. The normalization is computed using (5), where, x_{norm} represents the normalized feature, x is the original feature value, while x_{min} and x_{max} are the minimum and maximum values of the feature set, respectively.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (5)$$

4) Classification

This study compared the performance of three classifiers, namely SVM, BNN, and RF, aiming to identify the most accurate and efficient model. The classification process consisted of training and testing processes. The classification process involved both training and testing phases, using K-fold cross-validation with K = 4 for data division. The models were evaluated using the three datasets.

The primary objective of SVM is to identify the optimal separator function to distinguish between two data classes [23]. This function, known as the hyperplane, is determined through a learning process. SVM utilizes a linear separator function, shown in (6), where $f(x)$ is defined in (7), and $x, w \in R^n$ and $b \in R^n$ (R in scalar space, R^n in vector space). The mathematical formulation of the SVM optimization problem is presented in (8), where x_i represents the input values, while y_i denotes the output values, which can be 1 or -1. The parameters w and b are the variables to be determined. The objective is to minimize $\frac{1}{2}\|w\|^2$ or, equivalently, maximize $\frac{1}{\|w\|}$ or $w^T w$, subject to the constraint $y_i(wx_i + b) \geq 1$. SVM employs a linear kernel function, and the Sequential Minimal Optimization (SMO) algorithm is used to find the separating hyperplane.

$$g(x) = sgn\big(f(x)\big)g(x) \quad (6)$$

$$f(x) = w^T x + b \quad (7)$$

$$\min_{w,b} \frac{1}{2}\|w\|^2 \text{ to } y_i(wx_i + b) \geq 1, i = 1, \dots m \quad (8)$$

The BNN model is composed of neurons arranged across multiple layers [24]. Training a BNN uses the backpropagation algorithm, which employs gradient descent to minimize output errors [25]. The BNN architecture in this study consisted of two hidden layers and one output layer, as porttrayed in Figure 8. The first hidden layer has 100 neurons, the second hidden layer has 10 neurons, and the output layer consists of a single neuron. A binary sigmoid activation function is applied to the hidden and output layers. The training process used an error threshold of 0.001, with 1000 epochs and a learning rate of 0.1.

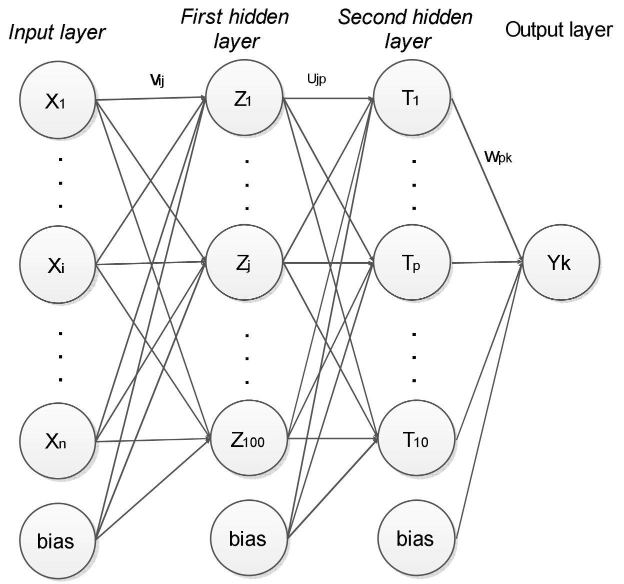

Fig. 8. BNN architecture in this study.

The output of the j^{th} neuron in the first hidden layer is calculated in (9). Here, n represents the number of neurons in the input layer, v_{0j} represents the weight of the bias towards the j^{th} neuron in the first hidden layer, x_i represents the j^{th} input signal, and v_{ij} represents the weight from x_i to neuron z_j in the first hidden layer. Then, the activation function with binary sigmoid, $f(z\_net_j)$, is applied to calculate its output signal using (10).

$$z\_net_j = v_{0j} + \sum_{i=1}^{n} x_i v_{ij} \quad (9)$$

$$z_j = f(z\_net_j) \quad (10)$$

This also applies to the second hidden layer. The output unit is calculated in (11), and then the activation function calculates its output signal using (12). Here, m represents the number of neurons in the second hidden layer, w_{0k} represents the weight of the bias to the output neuron, T_p represents the output signal of the p^{th} neuron in the second hidden layer, and w_{pk} represents the weight from T_p to the output neuron y_k.

$$y\_net_k = w_{0k} + \sum_{p=1}^{m} T_p w_{pk} \quad (11)$$

$$y_k = f(y\_net_k) \quad (12)$$

The Mean Square Error (MSE) is computed in (13). Backpropagation adjusts the weight values to minimize MSE, ensuring that the error is reduced through weight updates. Here, N represents the total test data, t_d represents the d^{th} target data, and p_d represents the d^{th} prediction data.

$$MSE = \frac{1}{N}\sum_{d=0}^{N}(t_d - p_d)^2 \quad (13)$$

RF, introduced in 2001 [26], differs from standard decision trees, in that each split at a node is made based on the best feature among a random subset of predictors [27]. The RF algorithm involves the following steps:

- First it describes n_{tree} bootstrap samples from the original data.
- For each bootstrap sample, a non-trimmed classification or regression tree is grown as follows: for each node, the best split among a randomly chosen subset of m_{try} predictors is selected.
- To classify new data, the predictions from all n_{tree} trees are aggregated.

The number of trees used in the RF classifier was 100.

C. *Evaluation Method*

Accuracy, calculated using (14), is the parameter used to assess the performance of the proposed method. T_{pos}, T_{neg}, F_{pos}, and F_{neg} denote true positive, true negative, false positive, and false negative, respectively [28].

$$Accuracy = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \quad (14)$$

III. EXPERIMENTS AND RESULTS

Classification tests were conducted for two main tasks: moving object classification and motorcyclist helmet detection. Each experiment evaluated the performance of three descriptor configurations: the proposed combined descriptor (HAAR + HOG + LBP), individual descriptors (HAAR, HOG, and LBP), and paired descriptors (HAAR + HOG, HAAR + LBP, and HOG + LBP). In addition, the study compared the performance of three classifiers, namely SVM, BNN, and RF.

A. *Testing of Moving Object Classification*

The moving object classification test was conducted using the DS_moving_object dataset, and the results are presented in Table I. When employing the SVM classifier, the proposed descriptor combination HAAR + HOG + LBP and HAAR + HOG achieved the highest accuracy among all tested configurations. In the case of the BNN classifier, HAAR + HOG performed the best among the other descriptors, while the proposed method ranked second. Meanwhile, the RF classifier demonstrated the best performance when using the proposed descriptor, surpassing both individual and paired descriptors. These results suggest that the integration of three descriptors slightly enhances classification accuracy compared to using single or paired feature descriptors.

TABLE I. TESTING RESULTS OF MOVING OBJECT CLASSIFICATION

Descriptor	Accuracy (%)		
	SVM	**BNN**	**RF**
HAAR	98.98	98.98	99.59
HOG	98.62	98.16	98.37
LBP	94.22	95.45	95.40
HAAR+HOG	99.49	99.44	99.54
HAAR+LBP	99.08	99.13	99.69
HOG+LBP	99.19	98.62	99.03
HAAR+HOG+LBP (Proposed)	99.49	99.29	**99.75**

B. Testing the Classification of Motorcyclists Wearing Helmet

The classification of motorcyclists wearing helmets was tested using two datasets: DS_motorcycle and DS_motorcyclist_head. The results for DS_motorcycle are presented in Table II. Among all descriptor-classifier combinations, the HAAR + HOG descriptor with the RF classifier achieved the highest accuracy of 94.13%. However, the proposed method HAAR + HOG + LBP outperformed the other combinations when using the SVM, and matched the performance of the HAAR + HOG combination when using the BNN classifiers.

TABLE II. TESTING RESULTS OF THE CLASSIFICATION OF MOTORCYCLISTS USING HELMET IN THE DS_MOTORCYCLE DATASET

Descriptor	Accuracy (%)		
	SVM	**BNN**	**RF**
HAAR	89.88	89.00	93.88
HOG	76.50	76.38	79.38
LBP	56.13	55.25	59.00
HAAR+HOG	92.88	92.75	94.13
HAAR+LBP	90.13	89.75	94.00
HOG+LBP	77.25	78.63	79.25
HAAR+HOG+LBP (Proposed)	93.13	92.75	93.25

The classification results on DS_motorcyclist_head are shown in Table III. Here, the proposed descriptor performed the best, achieving the highest accuracy of 96.75% using both the SVM and BNN classifiers. Moreover, the results when using the DS_motorcyclist_head dataset yield better classification accuracy compared to those when using the DS_motorcycle dataset, suggesting that using head-only images is more effective for detecting helmet usage.

TABLE III. TEST RESULTS OF THE CLASSIFICATION OF MOTORCYCLISTS USING HELMET IN THE DS_MOTORCYCLIST_HEAD DATASET

Classifier	Accuracy (%)
SVM	96.75
BNN	96.75
RF	93.00

The proposed method was compared with previous research, as depicted in Table IV. In [12], the proposed HOG as a descriptor and SVM as a classifier yielded 91.75% accuracy. Authors in [11] proposed the HOG descriptor and RF classifier, which resulted in 95.00%. Therefore, it can be concluded that the proposed method is higher than the two previous studies in terms of accuracy. A comparison of the computation time of the combination of descriptors and datasets using SVM can be seen in Figure 9.

TABLE IV. COMPARISON OF THE PROPOSED METHOD WITH PREVIOUS RESEARCH FOR THE CLASSIFICATION OF MOTORCYCLISTS IN HELMET USE

Method	Accuracy (%)
HOG+SVM [12]	91.75
HOG+RF [11]	95.00
Proposed model	96.75

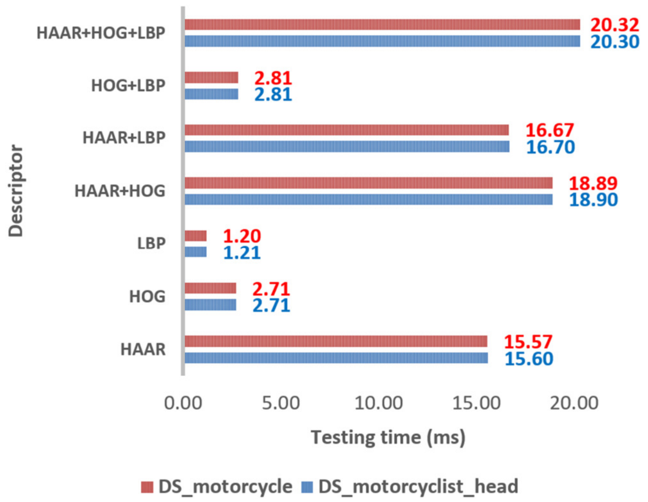

Fig. 9. Comparison of computation time for classification of motorcyclists wearing helmet.

The comparison reveals only a slight difference in classification time between the two datasets, indicating that either can be implemented in real-time applications. Among single descriptors, LBP recorded the fastest processing time, whereas HAAR was the slowest, taking approximately 13 times longer than LBP. HOG required about twice the time of HAAR. Among dual descriptors, the HOG + LBP combination was substantially shorter-lasting than the other two combinations. The HAAR+HOG+LBP descriptor takes 20.32 ms for DS_motorcycle and 20.30 ms for DS_ DS_motorcyclist_head. For this reason, it can be concluded that LBP as a single descriptor is more suitable for detecting motorcyclists not wearing helmets, which is related to the computation time used. Meanwhile, the combination of LBP and HOG as a double descriptor is better in computation time than the others.

IV. CONCLUSION

This study proposed a novel feature extraction approach by concatenating three descriptors—HAAR, Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP)—

to form a composite descriptor aimed at improving classification accuracy. This new descriptor was applied to two key classification tasks: moving object classification and helmet usage detection among motorcyclists. Both tasks are essential components in the development of an automated system for identifying motorcyclists who do not wear helmets. To evaluate performance, the proposed method was compared against individual descriptors (HAAR, HOG, LBP), as well as paired combinations (HAAR+HOG, HAAR+LBP, HOG+LBP). Additionally, three machine learning classifiers—Support Vector Machines (SVM), Backpropagation Neural Network (BNN), and Random Forest (RF)—were used to benchmark classification performance.

In the moving object classification task, the proposed method achieved the highest accuracy with the RF classifier, matched the performance of the HAAR+HOG combination with the SVM classifier, and ranked second when using the BNN classifier. In the helmet usage detection task, the proposed method consistently achieved the highest accuracy across both datasets when using the SVM and BNN classifiers.

These results indicate that the proposed method enhances accuracy compared to single (HAAR, HOG, LBP) and double descriptor combinations (HAAR+HOG, HAAR+LBP, HOG+LBP), at the cost of increasing computation time. This limitation can be mitigated by incorporating a feature selection process to reduce feature dimensionality and improve classification efficiency without compromising accuracy. Overall, the proposed approach demonstrates strong potential for real-time automatic detection of motorcyclists not wearing helmets.

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