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Classification of Helmet and Vest Usage for Occupational Safety Monitoring using Backpropagation Neural Network

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Abstract

Occupational Safety and Health (OSH) is a critical aspect in high-risk work environments, where the consistent use of Personal Protective Equipment (PPE) plays a vital role in preventing workplace accidents. However, non-compliance with PPE regulations remains a significant issue, contributing to a high number of work-related injuries in Indonesia. This study proposes an automated detection and classification system for PPE usage, specifically helmets and vests, using the Backpropagation algorithm in artificial neural networks. A total of 100 images were utilized, equally divided between complete and incomplete PPE usage. The dataset was split into 60% training and 40% testing. Image segmentation was performed using HSV color space conversion and thresholding, followed by RGB color feature extraction. The Backpropagation algorithm was then employed for classification. Experimental results show an average accuracy of 90%, with precision, recall, and F-measure all reaching 0.9. Despite some misclassifications due to color similarity between helmets and head coverings, the model demonstrated robust performance with relatively low computational requirements. This study contributes to the field of computer vision and intelligent safety systems by demonstrating the practical effectiveness of lightweight ANN architectures for PPE detection in real-time industrial scenarios, thereby highlighting the potential of backpropagation as an adaptive and practical alternative to more complex deep learning approaches for real-time PPE detection in occupational safety monitoring systems.

Keywords : *Backpropagation, Classification, HSV, Image Processing, Occupational Safety and Health, PPE Detection.*

1. INTRODUCTION

Occupational Safety and Health is a crucial aspect that must be considered in the workplace, especially in environments with a high risk of work-related accidents. One of the primary efforts to reduce the risk of accidents is the proper and consistent use of Personal Protective Equipment (PPE) [1]-[2]. PPE such as helmets, vests, protective shoes, and safety goggles is designed to protect workers from potential physical, chemical, and biological hazards that may occur in the workplace. One of the most critical components of Personal Protective Equipment (PPE) is the safety helmet, as it serves as the primary protection for the head against the risk of serious injury. The use of safety helmets can significantly reduce the impact of falling objects and other incidents that may jeopardize worker safety [3]-[6]. This is particularly important in work environments such as construction sites, which are known to have a high risk of occupational accidents. Worker safety at construction sites has increasingly become a major concern for many construction industries. Although the use of safety helmets has been

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proven effective in reducing injuries among workers, in practice, helmets are not always worn properly due to various factors.

Data from Jamsostek indicates that by the end of 2012, a total of 103,047 occupational accident cases had been recorded in Indonesia, with a consistent increasing trend in subsequent years [7]. This condition underscores the need for innovation in more effective and technology-based Occupational Safety and Health (OSH) monitoring systems. Therefore, there is a need for a system capable of automatically and accurately detecting and classifying the use of Personal Protective Equipment as part of an OSH monitoring framework. Such a system is expected to help improve worker compliance with PPE usage and reduce the incidence of occupational accidents in Indonesia.

The advancement of digital image processing and artificial intelligence technologies, particularly in the field of machine learning, offers effective solutions to address these challenges. One widely used method in classification tasks is the backpropagation algorithm, a training technique in artificial neural networks that accurately performs classification by learning from data. Many previous studies have been conducted to detect personal protective equipment using various methods, including both machine learning and deep learning approaches [8]-[11]. Mohammed Imran Basheer Ahmed et al. developed a PPE detection model based on Fast R-CNN, achieving a mean average precision (mAP) of 96% in real-time detection of eight PPE classes using the CHVG dataset [12]. Zijian Wang et al. developed and evaluated eight YOLO-based PPE detection models using a realistic CHV dataset, where YOLO v5x achieved the highest accuracy with an mAP of 86.55% and YOLO v5 demonstrated the fastest detection speed at 52 FPS, outperforming other methods on similar datasets [13]. Adban Akib Protik developed a real-time detector using the YOLOv4 model with a combined dataset to detect four classes of Personal Protective Equipment (PPE), achieving promising results with a mean average precision (mAP) of 79% [14]. Agung Susanto et al. conducted safety helmet detection using several image segmentation methods such as Sobel, Canny, and Otsu, as well as the SVM classification method, achieving an accuracy of 81% [15]. Zhaoyang Qiu et al. developed an enhanced YOLOv8 model by incorporating GhostConv layers to detect railway workers' safety helmets and vests. The research results show that the proposed model successfully improves detection accuracy with a 3.1% increase in mAP50 and 2.6% in recall, while also reducing the number of parameters by 1.4 million and the model size by 2.5 MB, outperforming the SSD model in terms of accuracy and computational efficiency [16]. The same method, YOLOv8, was used by Rizwaldi Muhamad Iman et al., achieving an accuracy of 90% [17]. The study by Febro Herdyanto et al. developed a CNN-based model using YOLOv8 for safety helmet detection in industrial settings with high accuracy, which can enhance safety through real-time monitoring and reduced manual inspections [18]. Tejas Bagthaliya and colleagues also developed a computer vision-based system that automatically detects and verifies the use of Personal Protective Equipment (PPE) using deep learning at construction sites to improve workplace safety [19]. Melike Çiftçi et al. compared YOLOv5 and YOLOv8 in Safety Equipment Detection on Construction Sites, with results showing that YOLOv8 performed better with a precision value of 87%, compared to YOLOv5 which achieved only 75% [20].

Based on related studies, this research employs the backpropagation algorithm due to its proven ability to optimize classification performance in artificial neural networks and its reliability in learning complex data patterns. Unlike other approaches that commonly utilize YOLO based detection methods or image segmentation, this study focuses on an efficient and interpretable approach using traditional Artificial Neural Networks (ANN) with backpropagation to detect the use of Personal Protective Equipment (PPE), particularly helmets and vests, in high-risk work environments.

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2. METHOD

This study utilizes the Backpropagation algorithm with the aim of training an artificial neural network to classify the use of personal protective equipment (PPE) as either complete or incomplete. The algorithm is employed due to its ability to learn patterns from training data and iteratively adjust network weights to minimize prediction errors. As a result, the developed model is expected to accurately recognize PPE usage patterns, even when the data is complex and non-linear. The research workflow is illustrated in Figure 1 below:

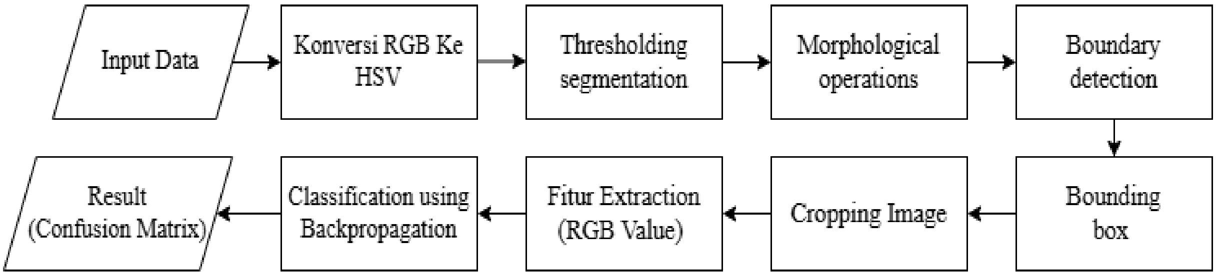

Figure 1. Methodological steps used in this study

The detailed explanation of the methodological steps used is as follows:

2.1. Data Collection

The dataset used in this study consists of 100 images, comprising 50 images of complete PPE usage and 50 images of incomplete PPE usage. These images are divided into two processes: training and testing. A total of 60% of the data, or 60 images, is used for training the model, while the remaining 40%, or 40 images, is used for testing to evaluate the model's performance in classifying new, unseen data. This division is carried out randomly to ensure that the evaluation results are more objective and representative of the model's generalization capability. An example of complete and incomplete PPE usage data is shown in Figure 2.

PPE User Image	Completeness Status
	Complete (0)
	Incomplete (1)

Figure 2. Sample Image of PPE User

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2.2. Object Segmentation

In the object segmentation stage, six steps are performed with the aim of identifying objects in the image for further processing with high precision. The steps involved in this stage include RGB feature extraction into HSV features, thresholding segmentation, morphological operations, boundary detection, bounding box generation, and image cropping. The Hue Saturation Value (HSV) color model is used in this study for image processing and object detection to enable more accurate color identification. HSV separates image intensity (Value) from color information (Hue and Saturation), making it more effective for analyzing and recognizing objects based on color[21]. The formula used to convert RGB values to HSV is as follows[22]:

$$H = \begin{cases} \dfrac{G - B}{Max - Min}\, x\, 60, & if\ R = Max \\ 120 + \left\{\dfrac{B - R}{Max - Min}\right.\, x\, 60, & if\ G = Max \\ 240 + \left\{\dfrac{R - G}{Max - Min}\right.\, x\, 60, & if\ B = Max \end{cases} \quad (1)$$

$$S = \frac{Max - Min}{Max} \quad (2)$$

$$V = Max \quad (3)$$

The maximum value (Max) is defined as the highest value among the three color components in the RGB color model, namely R (Red), G (Green), and B (Blue). Conversely, the minimum value (Min) refers to the lowest value among these components. Mathematically, this can be expressed as:

$$Max = \max(R, G, B)$$
$$Min = \min(R, G, B)$$

For the thresholding parameters, there are two parts: one for segmenting the body part (vest) and the other for segmenting the head part (helmet). Each part uses an upper and lower threshold value. For the head segment, the lower threshold is set at [0, 0, 200], and the upper threshold is [180, 30, 255]. For the body segment, the lower threshold is [30, 50, 50], and the upper threshold is [40, 255, 255].

The results of object detection using HSV based segmentation are shown in Figure 3 below:

RGB Image HSV

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Safety Vest Threshold | Safety Vest Bounding Box

Helmet Threshold | Helmet Bounding Box

Figure 3. Object Segmentation Process

2.3. Feature Extraction

After the segmentation process is completed, RGB (Red, Green, Blue) color feature extraction will be carried out for the helmet and safety vest regions. This extraction aims to obtain the average values of the color components in each segmented part. These RGB values will be used as input features in the next classification stage to recognize and differentiate whether the user is wearing complete or incomplete PPE. The results of the RGB color feature extraction are presented in Table 1 below, showing the average RGB values for each image in the respective body parts analyzed.

Table 1. The results of the RGB color feature extraction

Helmet RGB Values	Safety Vest RGB Values	Class
[161, 73, 72]	[187, 62, 55]	Incomplete
[177,165,161]	[141,127,118]	Incomplete
[218,181,177]	[232, 87, 75]	Incomplete
[180,161,154]	[185,158,147]	Incomplete
[215,185,183]	[229,73,58]	complete
[166,128,128]	[224,76,59]	complete
[205,166,163]	[184,189,110]	complete
[157,139,153]	[165,91,30]	complete

2.4. Classification using Backpropagation

The research method used is the Backpropagation algorithm, a supervised learning algorithm consisting of an input layer, hidden layers, and an output layer. This algorithm trains the artificial neural network by iteratively adjusting the connection weights between layers based on prediction errors, thereby minimizing the difference between the generated output and the actual target during the data classification process. In this study, the neural network configuration consists of one neuron in the input layer, six hidden layers, a maximum of 1000 epochs, and a learning rate (alpha) of 0.00001. The model was implemented using the Python programming language supported by the TensorFlow and Keras

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libraries, which provide flexible and high-level APIs for constructing and training artificial neural networks. in indonesia

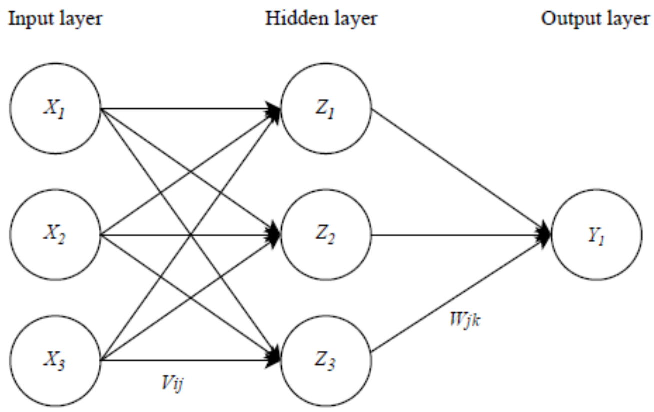

Figure 4. Architecture of Backpropagation ANN

Figure 2 depicts a typical architecture of a Backpropagation-based Artificial Neural Network (ANN). In this architecture, $\boldsymbol{x_1, x_2, x_3}$ serve as the input neurons, $\boldsymbol{z_1, z_2, z_3}$ form the hidden layer neurons, and $\boldsymbol{y_1}$ is the output neuron. The input layer neurons are connected to the hidden layer neurons through weighted links, as are the hidden layer neurons connected to the output layer neuron. The weights between layers are iteratively adjusted during the training process with the objective of minimizing the error [23]. The training of an artificial neural network using the backpropagation method consists of three main stages: the feedforward stage, the backpropagation stage, and the weight adjustment stage.

The following are the detailed steps of the backpropagation method [24]:

Initialize the epoch, the number of units in the input layer, hidden layer, and output layer; set the learning rate; and initialize all weights with small random values. If the stopping condition has not been met, proceed phase 1 - 3.

Phase 1: Feed forward

Each input unit $(\boldsymbol{x_i, i = 1, 2, 3 \ldots, n})$ receives an input signal $\boldsymbol{x_i}$ and transmits it to all neurons in the hidden layer
Each hidden unit $\left(\boldsymbol{z_j, j = 1, 2, 3 \ldots, p}\right)$ sums the weighted input signals using the following equation:

$$\boldsymbol{z\_in_j = v_{oj} + \sum_{i=1}^{n} x_i\, v_{ij}} \quad (4)$$

Calculate the activation using the sigmoid function:

$$\boldsymbol{z_j = f(z\_in_j) = \frac{1}{1 + e^{-z\_in_j}}} \quad (5)$$

The output from the activation function is transmitted to all units in the hidden layer.

Calculate the output at the output units $(\boldsymbol{y_k, k = 1, 2, 3 \ldots, m})$

$$\boldsymbol{y\_in_k = w_{ok} + \sum_{i=1}^{p} z_j\, w_{jk}} \quad (6)$$

Calculate the output signal using the sigmoid activation function:

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$$\boldsymbol{y_k} = \boldsymbol{f(y\_in_k)} = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e^{-y\_in_k}}} \quad (7)$$

Phase 2: Backpropagation

Each output unit $(\boldsymbol{y_k}, \boldsymbol{k} = \mathbf{1}, \mathbf{2}, \mathbf{3} \dots, \boldsymbol{m})$ receives the target pattern corresponding to the training input pattern and calculates the error information:

$$\boldsymbol{\delta_k} = (\boldsymbol{t_k} - \boldsymbol{y_k}).\boldsymbol{f'(y\_in_k)}$$

$$\boldsymbol{\delta_k} = (\boldsymbol{t_k} - \boldsymbol{y_k}).\boldsymbol{y_k}(\mathbf{1} - \boldsymbol{y_k}) \quad (8)$$

Calculate the weight correction (which will be used to update the weights).

$$\Delta\boldsymbol{W_{kj}} = \boldsymbol{\alpha\delta_k z_j} \; (\boldsymbol{k} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{m}\,;\; \boldsymbol{j} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{p}) \quad (9)$$

Calculate the δ factor for the hidden units based on the error at the hidden unit z_j.

$$\boldsymbol{\delta\_in_j} = \sum_{k=1}^{m} \boldsymbol{\delta_i}\, \boldsymbol{v_{kj}} \quad (10)$$

Factor of the hidden unit:

$$\boldsymbol{\delta_j} = \boldsymbol{\delta\_in_j}\,.\boldsymbol{f'(z\_in_j)}$$

$$\boldsymbol{\delta_j} = \boldsymbol{\delta\_in_j}\,.\boldsymbol{z_j}(\mathbf{1} - \boldsymbol{z_j}) \quad (11)$$

Calculate the weight update term v (which will later be used to adjust the weight v).

$$\Delta\boldsymbol{v_{ji}} = \boldsymbol{\alpha\delta_j x_i} \; (\boldsymbol{j} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{p};\; \boldsymbol{i} = \mathbf{0}, \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{n}) \quad (12)$$

Phase 3: Weight Adjustment

Calculate all weight updates. Weight updates directed toward the output units:

$$\boldsymbol{w_{kj}}\,(\boldsymbol{new}) = \boldsymbol{w_{kj}}\,(\boldsymbol{old}) + \Delta\boldsymbol{w_{kj}} \; (\boldsymbol{k} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{m};\; \boldsymbol{j} = \mathbf{0}, \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{p}) \quad (13)$$

Weight updates directed toward the hidden units:

$$\boldsymbol{v_{ji}}\,(\boldsymbol{new}) = \boldsymbol{v_{ji}}\,(\boldsymbol{old}) + \Delta\boldsymbol{v_{ji}} \; (\boldsymbol{j} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{p};\; \boldsymbol{j} = \mathbf{0}, \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{n}) \quad (14)$$

Check the stopping condition: if the desired error threshold or the maximum number of iterations has been reached.

2.5. Model Evaluation

The testing was conducted to evaluate the performance of the Backpropagation algorithm. The results of the system testing were then analyzed to assess the accuracy and effectiveness of the algorithm used. In this study, the evaluation metrics included accuracy, precision, recall, and F-measure. Accuracy is a measure of how close the obtained results are to the expected or true results. Precision refers to the degree of relevance of the information retrieved by the system in response to a user's query. Recall is the measure of a system's ability to retrieve relevant information. To calculate the values of performance metrics in percentage, the following equations can be used [25]:

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$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} x\ 100\% \tag{15}$$

$$Precision = \frac{TP}{TP + FP} x\ 100\% \tag{16}$$

$$Recall = \frac{TP}{TP + FN} x\ 100\% \tag{17}$$

3. RESULT

The results of testing using 100 image data, consisting of 50 images labeled as "complete" and 50 images labeled as "incomplete," are presented in this study. The dataset was divided into two parts: 60% used as training data and 40% as testing data. This testing scenario was designed to evaluate the system's performance in classifying images based on the predefined labels. The classification test results are shown in Table 2 below:

Table 2. The results of classification using Backpropagation

True Labels	**Predicted Labels**		**Accuracy**
	Complete	Uncomplete	
Complete	**17**	3	85%
Uncomplete	1	**19**	95%
Average Accuracy			**90%**

Based on Table 2, the testing results from 40 data samples show that 17 were correctly predicted as "incomplete" according to their actual labels, and 19 were correctly predicted as "complete." However, 3 samples with the actual label "complete" were incorrectly predicted as "incomplete," and 1 sample with the actual label "incomplete" was misclassified as "complete." These misclassifications occurred because the object in the image was wearing a white hijab, which resembled the color of the helmet, making it difficult for the system to distinguish between the two. As a result, the total average accuracy achieved in this study was 90%, with precision, recall, and F-measure values of 0.9.

4. DISCUSSION

This study emphasizes the use of the backpropagation algorithm as an adaptive and effective solution for detecting the use of Personal Protective Equipment (PPE), particularly helmets and vests, in high-risk work environments. This approach distinguishes the study from prior research, which has predominantly employed deep learning methods such as YOLOv7, YOLOv8, as well as image segmentation techniques and classification methods like Support Vector Machine (SVM). Several previous studies have demonstrated the effectiveness of deep learning for PPE detection. For instance, Mohammed Imran Basheer Ahmed et al. developed a PPE detection model based on Fast R-CNN, achieving a mean average precision (mAP) of 96% for detecting eight PPE classes using the CHVG dataset. Zijian Wang et al. compared eight YOLO-based models on the CHV dataset, reporting that YOLOv5 achieved the highest accuracy with an mAP of 86.55%, while YOLOv5 showed the fastest detection speed at 52 FPS. Similarly, Adban Akib Protik used YOLOv4 on a combined dataset and achieved a mAP of 79%. Agung Susanto et al. employed traditional image processing techniques, combining segmentation methods like Sobel, Canny, and Otsu with SVM classification, achieving an accuracy of 81%. While these methods are simpler and less computationally intensive than deep learning, their accuracy is generally lower. On the other hand, Zhaoyang Qiu et al. improved the YOLOv8 model by integrating GhostConv layers, resulting in a 3.1% increase in mAP50 and 2.6% in

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recall, while also reducing the model size by 2.5 MB and parameters by1.4 million—surpassing the SSD model in accuracy and efficiency. Rizwaldi Muhamad Iman et al. also applied YOLOv8 and achieved an accuracy of 90%. Febro Herdyanto et al. further developed a CNN-based model using YOLOv8 for real-time helmet detection in industrial settings. Meanwhile, Tejas Bagthaliya and Melike Çiftçi implemented computer vision systems that evaluated YOLOv5 and YOLOv8. Çiftçi's study showed YOLOv8 yielded better performance, with a precision of 87%, compared to YOLOv5 which achieved 75%. Although deep learning methods demonstrate high accuracy, implementation requires substantial computational resources and extended training times, which may pose challenges in real-world applications, particularly in field environments with limited computational infrastructure.

In contrast, this study demonstrates that the backpropagation algorithm, despite its relatively simple architecture, is capable of achieving competitive classification performance with an accuracy of 90%. This result highlights the potential of the algorithm as a lightweight and computationally efficient alternative to more complex deep learning techniques. Due to its adaptability to various training datasets and minimal hardware requirements, the backpropagation-based approach is particularly suitable for practical implementation in field-based safety monitoring systems, especially in environments where deploying deep learning infrastructure is not feasible. By leveraging the learning capabilities of Artificial Neural Networks (ANNs) and applying the backpropagation process for optimization, this study presents a simplified yet effective method for detecting Personal Protective Equipment (PPE), addressing the urgent need for efficient, real-time, and scalable safety solutions in high-risk occupational environments. However, while the model demonstrates promising performance under controlled testing conditions, its accuracy may decrease when applied to complex real-world scenarios, such as those involving poor lighting or partial occlusion of PPE elements. Therefore, future research could focus on developing hybrid models that combine traditional ANN with edge-enhanced preprocessing techniques to improve robustness and detection accuracy in a wider range of challenging field conditions.

CONCLUSION

This study has demonstrated that the backpropagation algorithm, implemented within an artificial neural network (ANN) architecture, is capable of effectively classifying the use of Personal Protective Equipment (PPE), specifically helmets and vests, with an average accuracy of 90%. The classification process was carried out following image segmentation using HSV color space conversion and thresholding, followed by RGB color feature extraction. Although a few misclassifications occurred primarily due to the visual similarity between white head coverings and helmets the system overall exhibited robust performance with relatively low computational demands. The primary strength of this approach lies in its lightweight architecture and computational efficiency, making it a practical solution for real-time safety monitoring in field environments with limited hardware resources. These findings highlight the potential of the backpropagation algorithm as a viable and adaptive alternative to more complex deep learning models, particularly in applications where resource constraints are a critical factor. The scientific contribution of this work is the validation of lightweight ANN architectures for vision-based PPE detection in industrial settings. This is highly relevant to the field of informatics, especially in the development of real-time safety systems that are scalable, efficient, and applicable in high-risk occupational environments. Future studies may explore real-time deployment using embedded systems such as Raspberry Pi or Jetson Nano and evaluate the model's performance on larger and more diverse datasets. Additionally, future research may investigate hybrid models that combine backpropagation with lightweight object detection algorithms to enhance generalizability and classification accuracy across various real-world scenarios.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest either among themselves or with the subject of this research.

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