On-Site Automatic Supervision Model for Helmet Detection using Improved Convolutional Neural Network

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Abstract: The safety of construction workers is becoming an increasingly important issue for various building sectors. Workers' compensation claims may be reduced if more of them wore safety helmets, yet improper use of helmets is a common problem on construction sites. Therefore, a system that can automatically identify safety helmets using computer vision is crucial. Although many studies have focused on helmet detection in general, few have specifically addressed its use in construction locations. In this paper, we have designed an on-site automatic supervision model for helmet detection using an improved convolutional neural network to determine whether people are wearing helmets or not on the construction site. In the proposed model, firstly, pre-processing of the input data image is done to enhance and extract the appropriate features from it. To achieve this goal, histogram equalization and the local binary pattern (LBP) algorithm are deployed. After that, a convolutional neural network (CNN) is applied for helmet detection, which classifies whether the helmet is worn or not. The proposed model is simulated on the standard dataset. The dataset contains two classes. The first class contains images without helmets, and the second class contains helmet images. Further, the visual quality of the input image and images generated after enhancement and feature extraction is shown in the qualitative analysis, whereas accuracy, precision, recall, and F-score are measured in the quantitative analysis. The result shows that the proposed model outperforms both classes and achieves high accuracy (0.95652).

Keywords: CNN, Detection, Helmet, LBP, Neural Network, On-site Automatic Supervision, Safety.

1. Introduction

Production and development initiatives are on the rise as urbanization continues to accelerate. Simultaneously, however, there is a growing concern for worker safety [1]. Foreign objects striking workers or bystanders or falling from great heights caused 69.6% of all construction safety accidents in China in 2019 [2]. This is according to survey data from the Ministry of Housing and Urban-Rural Development of the People's Republic of China. Similar to the findings of the US Occupational Safety and Health Administration (OSHA) in 2021, the UK Health and Safety Executive (HSE) reports that fatal incidents involving falling items will be most common in the construction sector in 2020 [3]. Simultaneously, similar challenges are being experienced by the traffic control division and other manufacturing sectors. The helmet is an important piece of safety gear for the head. When it comes to safeguarding employees' heads and successfully minimizing the fatality rate associated with safety accidents, wearing a helmet is essential. However, many accidents occur because employees either aren't aware of the requirements or choose not to comply with them by not wearing safety helmets as required. Because of factors including extensive work areas and people's tiredness, manual on-site monitoring of helmet use has a poor impact and cannot correctly oversee the helmet use of employees in real-time [4]. For this reason, more and more academics have taken an interest in the question of how to automatically monitor whether or not employees are wearing helmets on the job site. At present, machine learning and deep learning algorithms are used for on-site automatic helmet detection. Thus, in this paper, we have explored various machine learning and deep learning algorithms deployed for helmet detection. Based on the analysis, we have defined an on-site automatic supervision model for helmet detection using the improved convolutional neural network (I-CNN). The main contribution of the proposed on-site monitoring model for automatic helmet detection is summarized below.

- The proposed model efficiently detects the helmet and classifies it as worn or not.
- In the proposed model, pre-processing of the input image is done using histogram equalization and the local binary pattern method to enhance and extract the appropriate features from the image.
- The proposed model achieves high accuracy (0.95652 for classes 1 and 2).

The remaining paper is divided into five sections. Section 2 shows the existing automatic helmet detection methods. Section 3 explains the proposed on-site monitoring model for automatic helmet detection. Section 4 shows the results and discussion part, in which subjective, objective, and comparative analysis is performed. Finally, the paper concludes in Section 5.

2. Related Work

In this section, we have studied and analyzed the existing algorithms used to design automatic helmet detection.

Detecting helmets automatically is, at its core, an object detection issue, susceptible to solutions based on deep learning and computer vision. The area of computer vision has made great strides thanks to deep learning and its applications because of the computational approach and accuracy it brings to object recognition [5]. In the literature, convolutional neural networks (CNN) [6] and You Look Only Once (YOLO) [7–8] are the most preferred deep learning algorithms deployed for helmet detection. Further, the CNN algorithm is more explored and deployed over YOLO in helmet detection methods [8–10]. Moreover, some other variants of CNN algorithms, such as region-based CNN [11], faster CNN [12], are deployed for helmet detection.

3. Materials and Methodology

Figure 1 explains the main steps required to design an on-site monitoring model for automatic helmet detection. It contains data collection, enhancement, feature extraction, CNN-based deep learning, and performance analysis steps. A detailed description of these steps is given below to help understand the proposed on-site monitoring model.

- **Data Collection:** In the proposed model, we have used the standard dataset, which is available on Github under the category of safety-helmet-classifier-dataset [13]. The dataset is based on datafountain’s dataset. The dataset contains images with helmets (positive) and without helmets (negative).

- **Enhancement**: In the proposed model, enhancement of the input images is done so that appropriate features from the images are extracted. To accomplish this goal, the histogram equalization method is applied to enhance the input images. In the proposed model, we have used the in-built function of histogram equalization, which is available in MATLAB software [14].

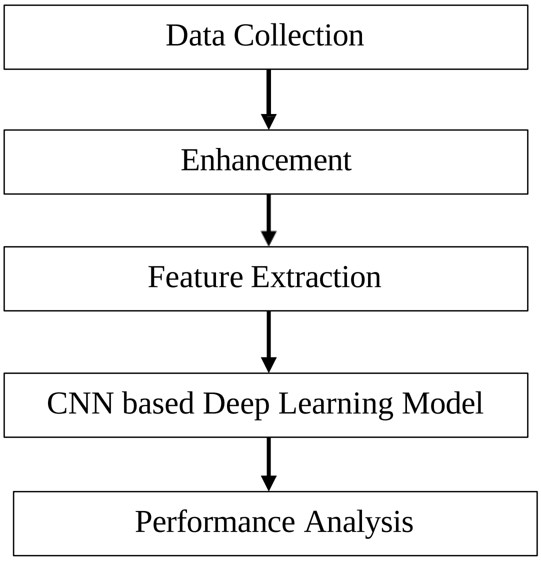

Figure 1 Block Diagram of Main Steps required for Design On-Site Monitoring Model

- **Feature Extraction**: The Local Binary Pattern (LBP) technique has seen widespread adoption in several domains [15]. Human face and emotion recognition were accomplished using the LBP algorithm. The Gabor maps of human faces are mined for LBP histograms. The resulting histograms are combined into a single vector. It is assumed that the vector represents some kind of pattern. When evaluating paper quality in different implementations, some researchers have used a Self-Organizing Map in conjunction with LBP texture characteristics. When describing textures, LBP is an operator that looks at the directions of distinctions between neighboring and center pixels. Calculating LBP values is shown as an example in Figure 2.

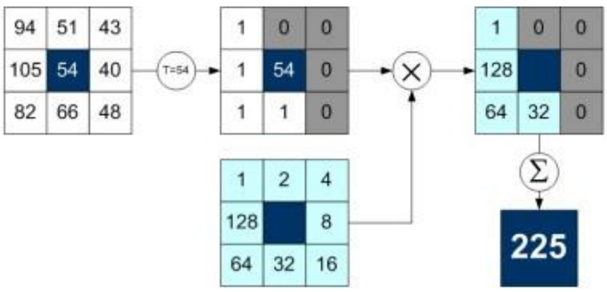

Figure 2 Steps for LBP Calculations

When the surrounding pixels are thresholded with the central pixel's value, a binary code is generated for each pixel in the image. One may interpret this binary pattern as a code. When the neighbor pixel's value is at or above the threshold, it is set to 1, and when it is below, it is set to 0. The frequency values of binary patterns will be calculated when the histogram has been built. A binary pattern may be represented by any one of these patterns. In LBP calculations, the amount of pixels used determines the number of histogram bins. LBP's utilization of 8 pixels results in a histogram with 2^8 bins, which is exactly 256.

In the simplest implementation of the LBP operator, the value of the central pixel is applied as a threshold to the values of its 3x3 neighbors. In order to represent texture features, a threshold operation will generate a binary pattern. Following is an elementary version of the LBP equation.

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n g(I_n - I(x_c, y_c)) \quad (1)$$

An LBP value at coordinates (xc, yc) is denoted as LBP(xc, yc). Pixel values in the immediate area (in) and in the middle (I(xc, yc)) are considered. Neighbouring pixels have an index of n. For negative x, the g(x) function returns zero, whereas for positive x, it returns one. In Figure 1 below, for instance, we'll choose the number 54 for the central pixel as our threshold. If the adjacent pixels' values are below the threshold, those pixels will be set to 0. Conversely, if the neighbouring pixels are higher or equal to the threshold, it changes to 1. Multiplying the binary matrix by the weight matrix yields the LBP value. A final representation of the LBP value is the sum of all product matrices. The LBP of the 3x3 matrix shown in Figure 1 is thus 225, which is the sum of the numbers $2^0+2^5+2^6+2^7$ =1+32+64+128. Researchers in the past have developed additional LBP techniques, such as vertical LBP (VLBP), circular LBP (LSB), advanced LBP (Advanced-LBP), and centre-symmetric LBP (CSLBP), by expanding the original LBP kinds by modifying the number of involved pixels and neighbour positions.

- **CNN-based Deep Learning Model**: The given CNN model can be used for helmet detection by training it on a dataset of images that contain both helmet and non-helmet examples. The model is designed to process grayscale images of size 64x64 pixels. During training, the model learns to extract relevant features from the input images using convolutional layers, followed by batch normalization and ReLU activation functions to introduce non-linearity. Max pooling layers are used to reduce spatial dimensions and capture important features. The final layers consist of a fully connected layer with a size equal to the number of classes (helmet and non-helmet) and softmax activation for classification. The model is trained using stochastic gradient descent with momentum (sgdm) as the optimization algorithm. The initial learning rate is set to 0.01, and the maximum number of training epochs is 10. The training data is shuffled every epoch, and the validation data (imdsTest) is used to monitor the model's performance. Validation is performed every 30 iterations. The training process does not display verbose output or generate plots. By training this model on a suitable dataset, it can learn to detect helmets in images and make predictions on new, unseen images, classifying them as either containing a helmet or not. The effectiveness of the model will depend on the quality and diversity of the training data and the complexity of the helmet detection task.
- **Performance Analysis**: The performance analysis of the proposed on-site monitoring model is done using qualitative and quantitative analysis. In the qualitative analysis, the visual quality of the helmet or person is shown in terms of the input image, after enhancement and feature extraction. On the other side, in the quantitative analysis, four performance metrics, accuracy, precision, recall, and F-score are measured to evaluate the proposed model. Next, how these performance metrics are calculated is shown in Table 1 [16–17].

Table 1 Performance Metrics

Parameters	Equation
Accuracy	$A = \frac{TP + TN}{TP + FP + TN + FN}$
Precision	$P = \frac{TP}{TP + FP}$

Recall	$R = \frac{TP}{TP + FN}$
F-Score	$F1 = \frac{2PR}{P + R}$

In Table1, TP, FP, TN, FN: denotes the true positive, false positive, true negative, false negative

Note:

- True Positives is the total number of occurrences that are true positive examples and were correctly identified as such by the classifier.
- The term "true negative" is used to describe the percentage of data points that are, in fact, incorrectly labelled as "negative" by the classifier.
- The term "False Positives" is used to describe the number of times a classifier incorrectly labels negative samples as positive.
- When a classifier incorrectly labels certain occurrences as negative when they should be positive, this is called a "False Negative."

4. Results and Discussion

This section shows the simulation results of the proposed on-site monitoring model for automatic helmet detection. The model is simulated in MATLAB. The hardware configuration is Intel(R)Core (TM)i7-7500CPU, 8GB RAM, 64-bit operating system. Table 2 shows the setup configurations of proposed model for enhancement, feature extraction, and CNN-based deep learning model is given.

Table 2 Setup Configuration of the Proposed On-Site Monitoring Model for Automatic Helmet Detection

Layer Name	**Size/Type**
imageInputLayer	[64 64 1]
convolution2dLayer	Filter size: 3x3, Filters: 8
maxPooling2dLayer	Pool size: 2x2, Stride: 2
convolution2dLayer	Filter size: 3x3, Filters: 16
maxPooling2dLayer	Pool size: 2x2, Stride: 2
convolution2dLayer	Filter size: 3x3, Filters: 32
fullyConnectedLayer	Size: Class
Training Parameter	**Value**
InitialLearnRate	0.01
MaxEpochs	10
Shuffle	'every-epoch'
ValidationData	imdsTest
ValidationFrequency	30
Verbose	false
Plots	'none'

4.1 Qualitative Analysis

Table 3 shows the visual quality of the input images and images are generated after enhancement and feature extraction.

Table 3 Qualitative Analysis for Helmet Detection

	N-Class=1	N-Class=2
Input Image		
Pre-Processed Image		
LBP Image		

4.2 Quantitative Analysis

Table 2 shows the qualitative analysis of the proposed model in terms of accuracy, precision, recall, and F-score. From the table, we found that the proposed model achieves 0.95652 (accuracy), 0.98765 (recall), 0.86957 (precision), 0.92486 (F-Score) for class 1 and 0.95652 (accuracy), 0.94495 (recall), 0.99517(precision), 0.96941 (F-score) for class 2.

Table 2 Quantitative Analysis of the Proposed On-Site Monitoring Model for Automatic Helmet Detection

N-Class	Accuracy	Recall	Precision	F-Score
1	0.95652	0.98765	0.86957	0.92486
2	0.95652	0.94495	0.99517	0.96941

Finally, Table 3 shows the comparative analysis of the proposed model with the existing automatic helmet detection model in terms of precision and recall.

Table 3 Comparative Analysis

	N-Class 1	
	Existing Model based on CNN	Proposed Model based on Improved CNN
Accuracy	0.94983	0.95652
Recall	0.9375	0.98765
Precision	0.88235	0.86957
F-Score	0.90909	0.92486
	N-Class 2	
Accuracy	0.94983	0.95652
Recall	0.95434	0.94495
Precision	0.97664	0.99517
F-Score	0.96536	0.96941

5. Conclusion

Helmet plays an important role for safety purposes on the construction site. Therefore, in this paper, we have designed on-site automatic supervision model for helmet detection using improved CNN. In the proposed model, initially, pre-processing of the dataset image is done for enhance the images using histogram equalization algorithm and extract the features using the local binary pattern (LBP) algorithm. After that, CNN algorithm is trained and tested using the pre-processed image. The CNN algorithm classifies the helmet is wear or not by people. The simulation result shows that the proposed model achieves high accuracy.

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