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Intelligent Access Control System For Safety In Industries

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Abstract

Industrial hazard may be defined as any condition produced by industriesthat may cause injury or death to personnel or loss of product or property. Safety insimple terms means freedom from the occurrence of risk or injury or loss.Industrial safety refers to the protection of workers from the danger of industrialaccidents.In some industries it is necessary for the workers to wear safety helmets and shoes while working. So to check weather workers are taking safety precautions ornot we are proposing this system. We can train our classifier to identify helmet andsafety shoes with clarifai API. There will be video streaming near the entry of theindustries where we can detect if person is wearing a helmet and shoes. If he iswearing them then the door will be open ,if he is not wearing then we can restricthis entry and we can warn him to wear by giving desired warnings throughspeakers..

Keywords:

Rasperry Pi;
Clarifai;
Camera face detection;
Helmet ;
Glasses,Gloves.

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1. Introduction

In the United States, numerous individuals work at jobsites under risky conditions, and thousands lose their lives each year. All things considered, the U.S. development industry experiences the high-est number of fatalities among all enterprises, i.e., one out of five specialist passings in private industry in 2014 were in development [35]. To place this into viewpoints, the quantity of laborer passings in development (9,836 out of 2005-2014) is even 44% more than the American war and military tasks fatalities (6,830 out of 2001-2014) in the previous decade [8]. Enormous misfortune has jumped out at the specialists' families, the industry, and the country: the normal of deadly word related wounds in development would speak to lost $5.2 million [27]. To secure the country's development workforce, techniques to enhance wellbeing perfor-mance estimation on building destinations is of principal significance [17].The causes of the construction site fatalities include falls, slips, being struck by objects, electrocution, and being caughtin/between objects [25]. And falls to a lower level are theleading hazards that have caused construction fatalities, ac- counting for one third of work deaths on construction sites [6]. In most of the fall incidents, the workers fall from heights and hit their heads on hard floors. In one study that investigated the number of construction fatalities and the use of safety equipment, the results showed that 47.3% of fatally injured victims either had not used safety equipment (e.g.,helmet, guard rails, etc.) or had not used them properly [1].Since the head is the most critical area of a human body and is the most vulnerable to an impact that could cause serious injury or death, the use of a protective helmet in construction work is required. However, the construction workers would not always follow the Occupational Safety and Health Ad- ministration (OSHA) regulations to wear head protection (e.g., helmet) whenever OSHA regulations require that they do so (e.g., under conditions of elevation). Therefore, methods to improve safety performance measurement on construction sites is of paramount importance [17]. Considering the large and increasing number of construction projects that are being conducted in the U.S. [7], there is a growing necessity of developing innovative methods to automatically monitor the safety for the workers at construction sites. Thanks to the widespread use of mobile sensors and new emerging sensor technologies, as well as the availability of data onvarious aspects of job bidding, construction equipment usage, and other data-driven applications, visual data surveillance on construction sites is exploding, and we have entered the era of big data construction. Surveillance of construction safety is now becoming more data driven [8]. In this paper, we aim to automatically detect the uses of construction helmets (e.g., whether the construction worker wears the helmet or not) by analyzing the construction surveillance images. Based on the collected images, we first detect the object of interest (i.e., construction worker) and further analyze whether the worker wears the helmet or not, by using computer vision andmachine learningtechniques.Detection of a construction worker with or without a safety equipment (i.e helmet) in construction surveillance images leads to identification of safety violations. Figure 1 shows two cases , where figure 1 (a) illustrates the positive example (construction worker with helmet) and Figure 1 (b) indicates the negative example (construction worker without helmet). In this paper, to automatically detect helmet uses for construction. Afterwards, the combination of color-based and Hough Transform feature extraction techniques is applied to detect helmet uses for the construction worker.

This work is innovative, in that it combines the emerging computer vision and machine learning techniques to create acollaborativeplatformforconstructionsafetyperformance measurement that helps to reduce constructionworkerfatalities andseriousinjuriesCausedbyfallstoalowerlevel.Thepro- totype developed in the paper is a first-of-its-kind system that allows the stakeholders (e.g., contractors,architects,engineers, builders and owner representatives) to monitor and detect the usesofhelmetsonconstructionsites.

The rest of this paper is organized as follows. Section II discusses the related work. Section III introduces the de- veloped system architecture and Section IV describes the proposed method in detail. Section V systematically evaluate the performance of our proposed method. Finally, Section VI concludes.

2. Research Method (12pt)

I.RELATED WORK

Construction WorkerDetection

The first step of our work is construction worker detec- tion from the collected construction surveillance images. The problem of human (e.g., construction worker) detection is toautomatically locate people in an image or video sequence, which has been actively investigated in the past decade. Human detection has variety of applications such as video- basedsurveillance,automatictagginginvisualcontentman- agement, autonomous driving [23], etc. The problem ofhuman detection has many challenges associated with it. The non- rigid nature of the human body produces numerous possible poses. It is also challenging to model simultaneouslyview (orientation) and size variations arisen from the change of the position and direction (e.g. tilt angle) of the camera.Unlike other types of objects, humans can be clothed with varying colors and texture, which adds another dimension of complexity. Furthermore, a significant percentage of scenes, such as urban environments, contain substantial amounts of clutter and occlusion[30].

Currently, the most prevalent approaches presented in the literatures are the detector-style methods, in which detectors aretrainedtosearchforhumanswithinanimageorvideo sequence over a range of scales. A number of these methods use global features such as Histogram of Oriented Gradient (HOG) descriptor [7], edge templates [12], while others build classifiers based on local features such as SIFT-like descriptors [22], Haar wavelets [36], and SURF-like descriptors [16]. Anotherfamilyofapproachesmodelshumansasacollection of parts [21], [28], [31]. Typically this class of approaches relies on a set of low-level features which produce a series of part location hypotheses. Subsequently, inferencesaremade with respect to the best assembly of existing part hypotheses. Approaches such as AdaBoost have been used with some degree of success to learn body part detectors such as the face [37],hands,arms,legs,andtorso[21],[29].Aconsiderable amount of works have also focused on shape based detection. Zhao et al. [41] used a neural network that was trained on human silhouettes to verify whether the extracted silhouettes correspond to a human subject. However, a potential disad- vantage of this method resides in the fact that they relied on depth data to extract the silhouettes. Others, such as Davis et al. [42] have also attempted to make use of shape-based cuesbycomparingedgestoaseriesoflearnedmodels.Wu et al. [39] have proposed learning human shape models and representingthemviaaBoltzmanndistributioninaMarkov Field.

Although a number of these methods have proved to be suc- cessful in detecting humans in the images, we have considered HOG descriptors because of their simple structure and high performance in human (e.g., construction worker) detection.

Helmet UseDetection

The literature of helmet use detection is very limited. It is considerably a new topic in computer vision and machine learning. Majority of the works focused on using color in- formation for helmet detection. Du et al. [10] described a combined machine learning and imageprocessingapproach for helmet detection in video sequences. In their framework, there were three major parts: the first was the person's face detection based on Haar-like face features [20]; the second was the motion detection and skin color detection usedto reduce the false alarms of faces; the third wasthe helmet detection using the color information above the face regions. For both the face detection and the helmet detection,they usedtheYCbCr[19]andHSV[32]colorspaces.Inasimilar work, Park et al. [26] exploited HOG features for human body detectionandsubsequentlyusedcolorhistogramsforhelmet detection. In another work, Wen et al. [38] proposed a circle detection method called Modified Hough Transformforhelmet detection for ATM's surveillancesystems.

In this work, we will explore to combine color-based and Circle Hough Transform (CHT) feature extraction techniques in order to develop a more robust and accurate helmet use detection system.

II SYSTEMARCHITECTURE

The overall system architecture for helmet use detection for construction safety is performed based on the construction surveillance images, which consists of three major compo- nents: image segmentation, object of interst (i.e., construction worker) detector, and helmet use detector, as illustrated in Figure 2.

Image Segmentation: For the collected images, ase- mantic image segmentation algorithm, such as Gaussian Mixture Model (GMM), is first applied to partition each of the relevant construction surveillance images into asetof object regions (e.g., scaffold, roof, sky, worker, etc).

*Object of Interst Detector:*After image segmentation, in order to recognize weather the segment object regions are construction workers, Discrete consine Transform (DCT) is computed to exact the frequency domain information from the spatial domain image, and then Histogram of oriented Gradient(HOG)features are drawn from the DCT coefficients. Resting on these features of the segmented regions, supervised classifier (i.e., Support Vector Machine (SVM) with linear kernel) is applied to detect whether there's construction worker in the image. (See Section IV-B for detail.)

Helmet Use Detector: After detecting the object of interest (i.e., construction worker in our application), a combination of color-based and Circle Hough Transform (CHT) feature extraction techniques is applied for helmet use detection. (See Section IV-C fordetail.)

III PROPOSEDMETHOD

ProblemDefinition

Based on the collected construction surveillance images after image segmentation (in our application ,we use Gaussian Mixture Model (GMM) for image segmentation, we represent our dataset.

The helmet detection problem can be specified as follows: given a dataset D as defined above, assign a label y(i.e., *human* or *non-human*) to an input image **x** through a classifier f ; for the images with *human* labels, furtheras- sign a label z (i.e., *with helmet* or *without helmet*) to each of them. Accordingly, in this paper, the proposed method can be divided into two steps: (1) construction worker detection, and (2) helmet use detection. In the first step, Discrete Cosine Transform (DCT) is used to extract frequency domain information from the segmented images and then Histogram of Oriented Gradient (HOG) features are extracted from the DCT coefficients. To predict whether construction worker is included in the image, the state-of-the-art supervised classifier Support Vector Machine (SVM) with linear kernel is used. After detecting the objects of interest (i.e., construction worker in our application), a combination of color-based and Circle Hough Transform (CHT) feature extraction techniques is exploited. Based on the color and shape information, the proposed method detects whether the construction worker wears helmet ornot.

Construction WorkerDetection

Discrete Cosine Transform: The Fourier transform de- composes a signal into its sine (imaginary) and cosine (real) components. The real part of the transform actually forms the Discrete Cosine Transform (DCT). The equation of

2D-DCT given by [24]is,This transform is used to compute the projection of an image into the orthogonal basis of cosine functions, resulting in aset of coefficients that represents the image in the real part of the spectral domain. In an image, a huge portion of signal energy lies in the low frequencies which appear in the upper left corner of corresponding DCT. From DCT of an image, distribution of energies in frequency domain can be found. This distribution should be different for human andnon-human segments. Using Histogram of Oriented Gradient (HOG), this differenceindistributionisfurthermeasured.

Histogram of Oriented Gradient: TheHistogramof Oriented Gradient (HOG) h

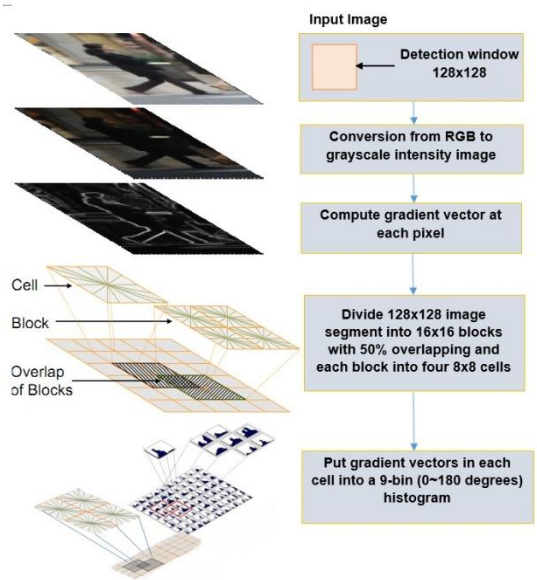


Fig. 3: HOG implementation scheme

human detector is one of the most popular and successful “human detectors”. It was introduced by Dalal and Triggs in [7]. HOG uses a “global” feature to describe a human rather than a collection of “local” features. This means that the entire human is represented by a single feature vector, as opposed to many feature vectorsrepresenting smaller parts of the human. HOG human detector uses a sliding detection window which is movedaround theimage. At each position of the detector window, a HOG descriptor is computed for the detection window. This descriptor is then showntoatrainedclassifier,whichclassifiesitaseither “human” or“non-human”.

In this paper, HOG features are computed for×the 128128 detection window. First, the gradient vector is com×puted at each pixel (both magnitude and angle) for this imagesegment.This128×128imagesegmentisthendividedinto16×16blockswith50%overlapping.Further,eachblockisdivided in four 8 8 cells. Then, the gradient vectors in each cell are put in a 9-bin (0-180 degrees) histogram. Note that *L*2 normalization method is used for normalizing the histogram to make it invariant to the illumina×on change. Tofurther illustrate, the 128128 pixel detection window isdivided into 15 blocks horizontally and 15 blocks vertically, fora total of 225 blocks. Each block contains 4 cells with a 9-bin histogram for each cell, for a total of 36 values per block. This brings the final vector size to 15 blockshorizontally

× 15 blocks verticall× 4 cells per block 9-b×ins per histogram = 8, 100 values. Figure 3 demonstratesthegeneral HOGimplementationschemestepbystep.

3).Support Vector Machine: SupportVectorMachine (SVM) is a method for the classification of both linear and nonlineardata[18].Itusesanonlinearmappingtotransformthe original training data into a higher dimension. Within this new dimension, it searches for the linear optimal separating hyperplane (i.e., a “decision boundary” separatingthe data pointsofoneclassfromanother).Withanappropriatenon- linear mapping to a sufficiently high dimension, data from two classes can always be separated by ahyperplane.The SVMfindsthishyperplaneusingsupportvectors(“essential” training data points) and margins (defined by the support vectors). SVM can be of linear and non-linear kernels. In our application, we apply linear SVM to classify two classes (human and non-human) due to its high efficiency. The output of a linear SVM is $u = w\ x$ b, where w is the normal weight vector to the hyperplane and x is the input vector. Maximizing themargincanbeseenasanoptimizationproblem:where$x$isthetrainingexampleand$y_i$isthecorrectoutput for the i_{th}trainingexample.

Figure 4 shows the detection flow of the construction worker. After image segmentation, DCT coefficient matrix of animageisusedinsteadofRGBimageastheinputtoHOGfeatures extraction scheme. Then, SVM classifieristrained with the HOG features extracted from human and non-human image blocks. Finally, this trained classifier is used to detect the object of interest (i.e., construction worker) in testing images. The implementation of the proposed construction worker detection method is given in Algorithm1.

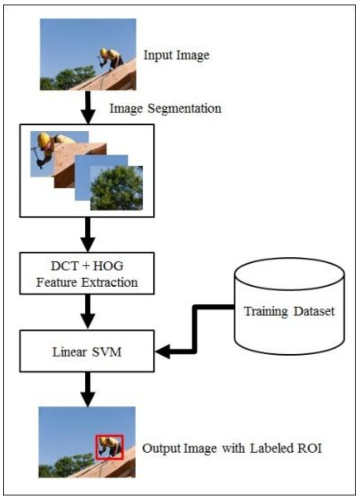


Fig. 4: Construction worker detection flow

Helmet UseDetection

Color-based Feature Extraction: After object of interest (i.e., construction worker) detection, we aim at searching for helmet use in the image segment to identify safety violation.In most of the construction surveillance images, it can be noticed thatcertaincolorsaremostfrequentlyusedforhelmets,such

Input: $D = \{\mathbf{x}_i, y_i\}^n_{i=1}$: training image set of n training
Image samples; D={X,Y}=1: testing images set of n testing images samples.
Output: The lables of all testing images human or non human.

Train a SVM classifier f (X) using n training image samples;
Partition images into a set of object regions ;
Partition images into a set of object regions ;
for each object region i do for each pixel (x, y) in i do
Using Eq. 1 to calculate 2D-DCT D(u, v);
End Calculate HOG features xi using DCT matrix of i;
End Using the classifier f (X) to detect construction worker in Dt;Algorithm 1: The algorithm for construction worker detec- tion.

as yellow, blue, red and white. Based on this observation, the proposed system is designed to recognize helmets made of these particular colors.

In the color-based feature extraction, threshold based color segment detection is used. For red and blue helmet detection, thresholds for only red and blue colors are set respectively. But for yellow color detection, thresholds for both red and green colors are required. Blue is not dominant as red and green in yellow color. Binary images are generated from red and green color planes using thresholds. Then common region in these two binary images is extracted, which belongs to yellow region. At last stage color information is retrieved for this region from the original RGB image. For white color detection, a common threshold for all three color components (red, green and blue) are used. Figure 5 shows an example of yellow color helmet detection using color-based feature extraction.

Our proposed algorithm searches for one of the four afore- mentioned color regions in the detected object of interest (i.e., construction worker) sequentially. Once it detects a particular color regions, it computes Hough Transform to find circles in those regions (introduced in the following section). If any circleisdetected,itisconsideredasahelmet.

Circle Hough Transform: In general, Hough Transform is a voting scheme to detect certain shapes in images such as lines, squares, circles, etc. In fact, it is a feature extraction technique used in image analysis, computer vision, and digital image processing. The purpose of Circle Hough Transform (CHT) is to find possible circular shapes in images [40]. The circlecandidatesareproducedby“voting”inHoughparameter space. Then the local maxima in a matrix of candidates is picked. If (a, b) is the center and r is the radius of a circle, thenthecirclecanbedefinedbythefollowingequation:

$$(x-a)^2+(y-b)^2=r^2$$

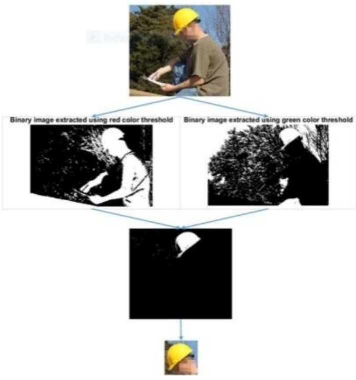


Fig. 5: Detection of helmet with yellow color

In CHT, at first the picture is changed over to paired (high contrast) utilizing an edge location system, for example, vigilant edge locator [9]. The subsequent stage is to discover a few points that are contender for the focuses of the circles for a given sweep. Presently if there are numerous radii (littler than the first) for that settled point, at that point there will be a few settled circles inside this circle. The framework proposed in this paper utilizes CHT to distinguish the hover shape around a cap. After shading based element extraction, it endeavors to discover hover shape in the picture section. First the slanting length d of the picture fragment is determined utilizing Pythagorean Theorem. At that point a level of the inclining length is considered as a scope of radii. Most extreme (Rmax) and least (Rmin) of this range are estimated utilizing the accompanying conditions:

$R_{max}=ceil(0.80\times d)$ -----(4)
$R_{min}=ceil(0.06\times d)$ -----(5)

where the qualities 0.80 and 0.06 for Rmax and Rmin are found experimentally. At that point, every one of the circles that fall inside Rmin and Rmin will be stamped. Figure 6 (a) demonstrates the separated shading district from the distinguished development specialist and (b) demonstrates the recognized hover of the cap in that section utilizing CHT. Figure 7 demonstrates the general stream of protective cap use identification.

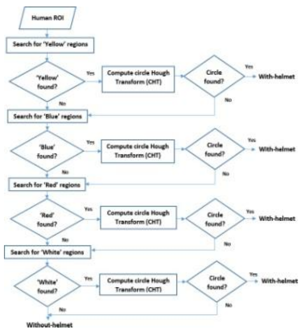
Also, the execution of the proposed protective cap use recognition strategy is given in Algorithm 2.

3. Results and Analysis

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2], [5]. The discussion can be made in several sub-chapters.

3.1. Sub section 1

Sub section should be written without bold type. The result and analysis are presented by present form. Please avoid too many paragraph in this section.



3.2. Sub section2

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IV.EPERIMENTAL RESULTS AND ANALYSIS

In this segment, to experimentally approve the proposed strategy, we lead two arrangements of trials dependent on the gathered picture test set portrayed in Section V-A: (1) In the primary arrangement of investigations, we look at our proposed technique for human (i.e., development laborer) identification with the technique utilizing

Fig. 6: Helmet circle detected by CHT

HOG only; (2) In the second set of experiments, we further assess the effectiveness of our proposed helmet use detectionmethod by comparison with the method merely using CHT

A.*ExperimentalSetup*

In data collection stage, the construction images are col- lectedfromdifferentwebsites([13],[14],[3],[4],[33],[34],[15], [5]). As manual image collection would be timeconsum- ing, an image crawler is built to automatically collect imagesfrom a given site. We build up a crawler that separates the source codes from the URL of the site and looks for some catchphrases, fundamentally some picture augmentations like ".jpg", ".png" and so forth. At that point it removes the picture URL that contains the objective catchphrases, and download the relating pictures. The created crawler downloads every one of the pictures found in the given sites including both development pictures and some other pointless pictures. At information cleaning stage, the undesirable pictures are separated physically. Basically, around 10, 000 pictures are gathered. Subsequent to performing information

Fig. 7: Helmet use detection flow

cleaning, 1, 000 pictures are chosen for further investigations.

Input:D_t={$\mathbf{x}_i$,y_i,z_i}^{n_t}: $n_t$image segments with
detected construction worker (i.e., y_i= *human*
for each image *i*).
Output:The labels for the testing images: with or withouthelmet
for each image in Dt do
Calculate d using Pythagorean Theorem; Calculate Rmin and Rmax;
Apply color-based method to extract color region c;
switch(c);
case “Yellow” ;
Compute CHT to find circles with radius r;
if r (Rmin, Rmax) then
return “with-helmet”;
end
case “Blue” ;
Compute CHT to find circles with radius r;
if r (Rmin, Rmax) then
return “with-helmet”;
end
case “Red” ;
Compute CHT to find circles with radius r;
if r (Rmin, Rmax) then
return “with-helmet”;
end
case “White” ;
Compute CHT to find circles with radius r;
if r (Rmin, Rmax) then

return “with-helmet”;
end
default return “without-helmet”;
end

Algorithm 2: The algorithm for helmet use detection

To prepare the classifier for human (i.e., development specialist) location, 354 human and 600 non-human example pictures are removed from the dataset. To set up this preparation set, in light of the gathered development pictures, Gaussian Mixture Model (GMM) is abused for picture division. Human examples are of various stances, as in building site pictures laborers are observed to be in various stances dependent on what they are doing. Non-human examples fundamentally involve development instruments, structures, rooftops, sky, and trees and so forth that are normally found in development pictures. For testing, we further gather 200 development pictures, 67 of which are labeled as "with-head protector", 83 are "without-cap" and 50 are labeled as "non-human". The gathered information is depicted in Table I. We assess the execution of various techniques utilizing the measures appeared Table II.

B. Evaluation of Construction Worker Detection

For human (i.e., development specialist) discovery, HOG fea-tures extricated from DCT coefficients of the pictures are sustained to the straight SVM classifier. We analyze our proposed strategy for human (i.e., development specialist) discovery with the technique utilizing HOG as it were. In view of the preparation informational collection with 354 human and 600 non-human picture fragments, we direct 10-folds cross approval for assessment. The outcomes appeared Table III and Figure 8 demonstrate that separating HOG highlights from DCT coefficients of the picture is progressively viable in human (i.e., development specialist) location than utilizing HOG as it were.

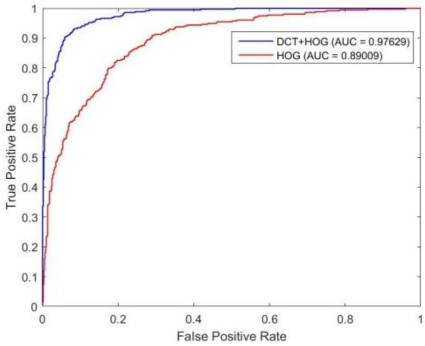

Fig. 8: ROC curves of different human detection methods

C.Evaluation of Helmet Use Detection

In this arrangement of tests, we further assess the perfor-mance of the proposed protective cap use location strategy. After the location of object of intrigue (i.e., development laborer), the blend of shading based and Circle Hough Transform (CHT) include extraction methods is connected to identify head protector utilizes for the development specialist. In view of the 200 testing pictures (67 of which are labeled as "with-protective cap", 83 are "without-head protector" and 50 are labeled as "non-human"), we contrast our proposed technique and the strategy utilizing CHT as it were. The exploratory outcomes appeared Table IV and V exhibit that mix of shading based and CHT highlight extraction procedures beats utilizing CHT just in protective cap use identification. As same human identification calculation is utilized in the two cases, precision rates in recognizing human and non-human are same. Subsequent to recognizing human articles (i.e., development specialists), as appeared Table V, in distinguishing protective cap, the ace presented technique gives better exactness (79.1%) than the standard (67.16%); in addition, the proposed strategy is progressively effective in identifying the instance of development laborer without head protector with 84.34% precision, while for benchmark strategy it is just 45.78%. CHT attempts to locate every conceivable hover in the picture, while consideration of shading data expands the precision of recognition of the nearness of the head protector. Without the shading data, it neglects to recognize round protective cap and human head as roundabout shape. That clarifies the purpose for the enormous distinction in distinguishing the instance of development specialist without head protector.

TABLE IV: Comparisons of different helmet use detection methods

Method	ACC(%)
CHT(baseline)	61.0
Color +CHT(proposed)	**81.0**

4. Conclusion (10pt)

In this paper, a novel methodology is proposed for programmed de-tection of protective cap utilizes for development security utilizing PC vision and machine learning procedures. The proposed framework has two noteworthy parts: one section joins recurrence area data of the picture with a famous human identification al-gorithm HOG for human (i.e., development laborer) location; the other part works for head protector use recognition consolidating shading data and Circle Hough Transform (CHT).

As of now, our framework can identify head protectors made out of some specific hues, for example, yellow, blue, red, and white. As an expansion of this work, we mean to make the framework versatile to recognize head protectors with different hues. In future, the framework will be made well equipped for separating between typical top and protective cap, as the proposed framework demonstrates low execution for this situation. Additionally, we intend to apply some profound learning procedures for enhancing the general precision of the framework. Likewise, applying chest area looking calculation as opposed to distinguishing entire human as object of intrigue can enhance the protective cap recognition exactness.

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Disclaimers: The findings and conclusions in the report are those of the authors and do not necessarily represent the views of the National Institute for Occupational Safety and Health (NIOSH). Mention of company names or productsdoesnotimplyendorsementbyNIOSH.

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