AUTOMATIC VEHICLE NUMBER IDENTIFICATION USING DIGITAL IMAGE PROCESSOR (DIP)

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ABSTRACT

Road accidents are one of the major causes of human deaths. Most of the deaths in accidents are due to damage to the head of the motorcycle riders. Among the different types of road accidents, motorcycle accidents are common and cause severe injuries. To reduce the involved risk for the motorcycle riders, it is exceptionally fascinating to utilize helmet. The helmet is the motorcyclist's main protection. Most countries require the use of helmets by motorcyclists, but many people fail to obey the law for various reasons. We present the development of a system using deep convolutional neural networks (CNNs) for finding motorcyclists who are violating helmet laws. The system comprises motorcycle detection, helmet vs. no-helmet classification and counting process. Faster R-CNN with ResNet 50 network model is implementing for motorcycle detector process. CNN classification model proposes for classify the helmet vs. no-helmet. Finally making alarm sound to alert the officer to preventing motorcycle accident. We evaluate the system in terms of accuracy and speed and identify the number plate of the vehicle.

1. INTRODUCTION

One of the leading causes of unnatural deaths today is road fatalities, primarily motorcycle accidents. Particularly, among all road fatalities, motorcycle accidents accounted for 9% in Europe, 20% in the United States, and 34% in western Pacific and Southeast Asian countries. Helmets are the main protection device for motorcyclists, so where compliance is low, automated processing has the potential to dramatically increase compliance, thereby saving human lives. Until very recently, most of the methods used for object detection and object classification used methods such as Haar, HOG, local binary patterns (LBP), the scale invariant feature transform (SIFT), or speeded up robust features (SURF) for feature extraction and then support vector machines (SVM),random forests, or AdaBoost for the classifier. Silva et al. use methods such as histograms of oriented gradient (HOG), LBP, and the wavelet transform (WT) for feature extraction for classifying motorcyclists with helmets and without helmets. They use multiple combinations of the base features such as HOG+LBP, HOG+WT, LBP+WT, and HOG+LBP+WT, obtaining seven possible feature sets. They combine the seven features with six classifiers, namely SVM, radial basis function network (RBNF), multilayer perceptron (MLP), naive Bayes, random forest, and k-nearest neighbours (KNN). On a test set dataset, the MLP classifier using HOG descriptors showed the result, with 91.3% accuracy.Traditional model only gives 91.3% accuracy. As convolutional neural networks (CNNs) have recently outperformed custom feature-based methods in many domains, there is evidence that the use of CNNs could increase the accuracy of helmet/no-helmet classification.

2. LITERATURE SURVEY

[1]. **Automatic detection of motorcyclists without the helmet.**

This paper aims to explain and illustrate an automatic method for motorcycles detection and classification of public roads and a system for automatic detection of motorcyclists without the helmet. For this, a hybrid descriptor for features extraction is proposed based on Local Binary Pattern, Histograms of Oriented Gradients and the Hough Transform descriptors.

[2]Machine Vision Techniques for Motorcycle Safety Helmet Detection.

This paper presents a system which automatically detects motorcycle riders and determines that they are wearing safety helmets or not.The system extracts moving objects and classifies them as a motorcycle or other moving objects based on features extracted from their region properties using K-Nearest Neighbor (KNN) classifier. The heads of the riders on the recognized motorcycle are then counted and segmented based on projection profiling.The system classifies the head as wearing a helmet or not using KNN based on features derived from 4 sections of the segmented head region. Experiment results show an average correct detection rate for near lane, far lane, and both lanes as 84%, 68%, and 74%, respectively.

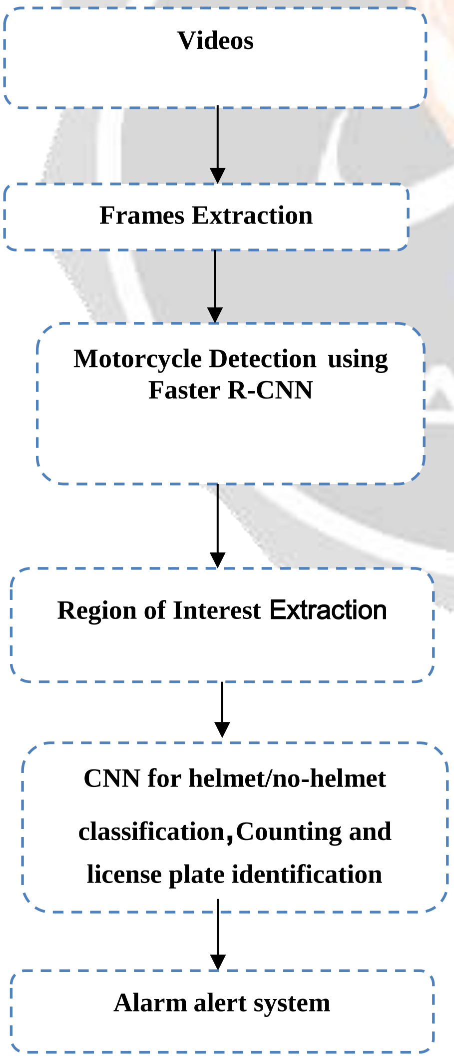
[3] Automatic Detection of Bike-riders without Helmet using Surveillance Videos in Real-time.

In this paper, they proposed an approach for automatic detection of bike-riders without helmet using surveillance videos in real time. The proposed approach first detects bike riders from surveillance video using background subtraction and object segmentation. Then it determines whether bike-rider is using a helmet or not using visual features and binary classifier. In order to evaluate the approach, they have provided a performance comparison of three widely used feature representations namely histogram of oriented gradients (HOG), scale-invariant feature transform (SIFT), and local binary patterns (LBP) for classification.

3. PROPOSED SYSTEM:

Video feeds are first run through a motorcycle detector.Second, frames are extracted from feed video.Third, each frame passed into motorcycle detection process. Faster R-CNN with ResNet 50 network model is implementing for motorcycle detection. Finally, detected region is passed to a CNN for helmet and no-helmet classification. Motorcycle detections classified as helmet violations are further processing and counting the motorcycles with helmet and no-helmet processing.

3.1 PROPOSED SYSTEM BLOCK DIAGRAM:



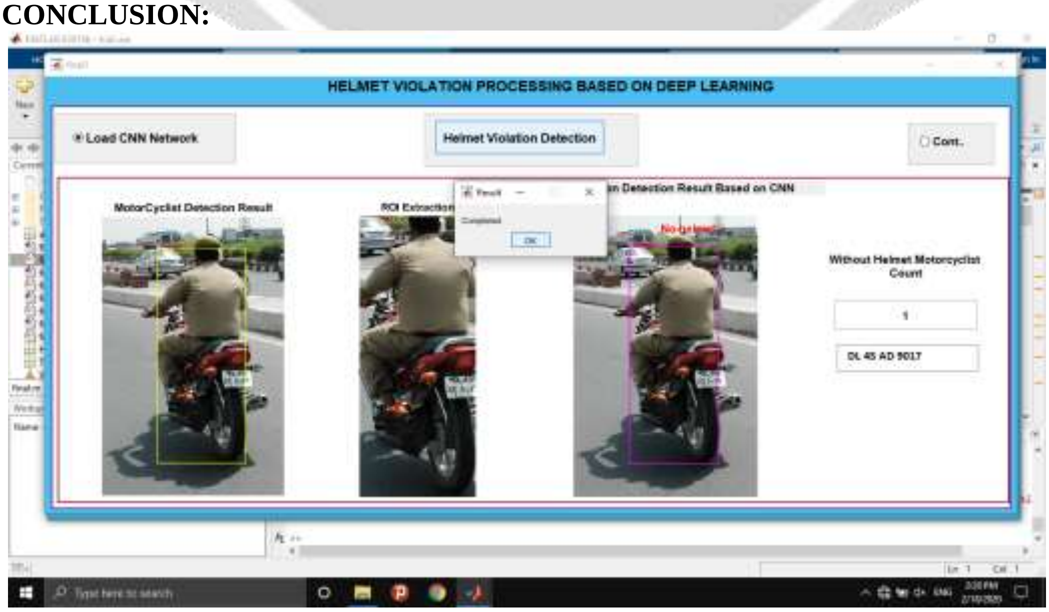
3.2 BLOCK DIAGRAM EXPLANATION

In this process initially the input to the system is a video file that is obtained from the public database.After the video acquisition is done from the public database, frames extraction is performed on the video that is acquired.After the video is acquired and the frame extraction is done motorcycle detection is implemented to each frame of video. Faster R-CNN with ResNet 50 model is used for detect the motorcycles in each frame. After that detected motorcycles are cropped for further process. Cropping process is called as ROI region extraction.After the motorcycle detection, we propose the helmet violation detection. Motorcycle ROI region is given to AlexNet CNN for classify the motorcycles with helmet and no-helmet. Proposed method shows how to use transfer learning to retrain AlexNet, a pretrained convolutional neural network, to recognize a new set of images. Transfer learning is commonly used in deep learning applications. Fine-tuning a network with transfer learning is usually much faster and easier than training a network with randomly initialized weights from scratch. The network has learned rich feature representations for a wide range of images. The AlexNet has 25 layers. In that, we proposed counting of no- helmet motorcyclist and alert to safety management system.

3.3. WORKING PRINCIPLE:

1. **Video Acquisition & Frames Extraction:**
   Test traffic videos are collecting from public database. After the video acquisition, frames extraction is performed.
2. **Motorcycle Detection:**
   Motorcycle detection is implemented to each frame of video. Faster R-CNN with ResNet 50 model is used for detect the motorcycles in each frame. After that detected motorcycles are cropped for further process. Cropping process is called as ROI region extraction.
3. **Helmet Violation Detection:**
   After the motorcycle detection, we propose the helmet violation detection. Motorcycle ROI region is given to AlexNet CNN for classify the motorcycles with helmet and no-helmet. Proposed method shows how to use transfer learning to retrain AlexNet, a pretrained convolutional neural network, to recognize a new set of images. Transfer learning is commonly used in deep learning applications. Fine-tuning a network with transfer learning is usually much faster and easier than training a network with randomly initialized weights from scratch. The network has learned rich feature representations for a wide range of images. The AlexNet has 25 layers.
4. **Counting & Alert System:**
   This is the last module of our work. In that, we proposed counting of no- helmet motorcyclist and alert to safety management system.

4. CONCLUSION:



The proposed framework for HELMET VIOLATION PROCESSING SYSTEM makes use of Faster R-CNN with ResNet-50 which is invariant to various challenges such as illumination, poor quality of video, etc. The use of the CNN for automatic learning of discriminative representations for classification tasks improves the classification rate and reduces the false alarms resulting into more reliable system. The experiments on videos obtained more detection, classification and counting accuracy and less false rate and thus shows the efficiency of the proposed approach.

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