Automatic Number Plate Recognition for Motorcyclists Riding Without Helmet

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***Abstract*—Motorcycles have always been the primary mode of transport in developing countries. In recent years, there has been a rise in motorcycle accidents. One of the major reasons for fatalities in accidents is the motorcyclist not wearing a protective helmet. The most prevalent method for ensuring that motorcyclists wear helmet is traffic police manually monitoring motorcyclists at road junctions or through CCTV footage and penalizing those without helmet. But, it requires human intervention and efforts. This paper proposes an automated system for detecting motorcyclists not wearing helmet and retrieving their motorcycle number plates from CCTV footage video. The proposed system first does background subtraction from video to get moving objects. Then, moving objects are classified as motorcyclist or non-motorcyclist. For classified motorcyclist, head portion is located and it is classified as helmet or non-helmet. Finally, for identified motorcyclist without helmet, number plate of motorcycle is detected and the characters on it are extracted. The proposed system uses Convolutional Neural Networks trained using transfer learning on top of pre-trained model for classification which has helped in achieving greater accuracy. Experimental results on traffic videos show an accuracy of 98.72% on detection of motorcyclists without helmet.**

Keywords—helmet detection; number plate recognition; computer vision; machine learning; convolutional neural networks; transfer learning

I. INTRODUCTION

In countries like India, Brazil, Thailand, majority of population uses motorcycles for daily commute. In India, as of 31 March 2015, there were 154.3 million registered motorcycles. In most of these countries, wearing helmet for motorcyclists is mandatory by law. Also, considering safety of people using motorcycles, wearing helmet is paramount. The MAIDS (Motorcycle Accidents In Depth Study) report [1], which was carried out in five European countries (France, Italy, Netherlands, Spain and Germany), mentions on page 122 that, in 68.7% of motorcycle accidents reported, helmet could have prevented or reduced the head injury sustained by the motorcyclist.

Currently, in practice, Traffic Police are entrusted with the task of ensuring that motorcycle riders wear helmet. But, this method of monitoring motorcyclists is inefficient due to insufficient police force and limitations of human senses. Also, all major cities use CCTV surveillance based methods. But, those require human assistance and are not automated.

Due to the increasing number of motorcycles and the concern for human safety, there has been a growing amount of research in the domain of road transport. The system proposed in this paper automates the task of monitoring motorcyclists. The system detects motorcyclists not wearing helmets and retrieves their motorcycle number plate in real time from videos captured by CCTV cameras at road junctions by making use of Machine Learning and Computer Vision techniques. Classifiers are built using Convolutional Neural Networks.

II. RELATED WORK

The predominantly used features in the field of computer vision are Hough transform, Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG) and Scale Invariant Feature Transform (SIFT). Hough transform is used to find geometric shapes like circles, ellipses in images. HOG [2] describes the local object shape and appearance in an image using distribution of edge directions or intensity gradients. LBP describes the local texture structure in image. SIFT tries to capture key-points in an image and extracts feature vectors for each key-point.

The first proposed and tested automated system for detection of motorcycle riders not wearing helmet was done by Chiverton [3]. The system uses SVM classifier trained on features derived from image data near head region of motorcyclists. The features selected capture the shape and reflective property of helmets where the top half of helmet surface is found to be brighter than the bottom half of the helmet. It also takes into account the circular arc-shape of helmet. The system uses circular arc detection technique based on Hough transform [20]. The main shortcoming of this approach is that it leads to a lot of mis-classification, as some objects which look similar to helmet get classified as helmets and some helmets which are different do not get classified as helmets. Another limitation is that it does not first identify motorcyclists in the frames, which should have been done, since helmet is only relevant in case of motorcyclists.

To overcome the problem of mis-classification, Silva *et al.* [4], [6] developed a system which first identifies motorcyclists in the frame using SVM classifier trained on features extracted by LBP descriptor. After that, helmet classification is done using SVM on features extracted by a hybrid descriptor, which is created by combining Circular Hough transform, HOG and LBP descriptors.

In parallel with Silva's work, Waranusast *et al.* [5] developed a system that uses K-Nearest Neighbors (KNN) classifier on features extracted from region properties in an image. For KNN classifier for motorcycle classification, the features considered are area of bounding rectangle and aspect ratio of the bounding rectangle. For KNN classifier for helmet classification, features like arc circularity (similarity between a circle and an arc) and average intensity of pixel are considered. But, the images captured in this system did not involve any occlusion as the images were perpendicular to the camera. So, this system did not consider solving problem of occlusion.

In [7], Doungmala *et al.* proposed a system for half helmet and full helmet detection using decision tree classifier with AdaBoost. The system first uses haar cascade features for face detection for classifying between without helmet and full helmet. Then, it uses circle hough transform for classifying between without helmet and half helmet. This system has limited scope as it involves video with very sparse traffic. Also, it does not take into account step of detecting motorcycles first, instead directly tries to detect helmet.

In [8], Jie Li *et al.* proposed a system for safety helmet detection for pedestrians at power substations. This system first does background modeling to find region of interest. After this, HOG features are extracted and SVM classifier is used to classify pedestrians. Finally, for the identified pedestrian, safety helmet classification is done by color feature recognition.

In [9], K. Dahiya *et al.* came up with helmet detection from surveillance videos where they used an SVM classifier for classifying between motorcyclist and non-motorcyclist and another SVM classifier for classifying between helmet and without helmet. For both classifiers, three widely used features - HOG, SIFT and LBP - were implemented and the performance of each was compared with that of other two features. They concluded that HOG descriptor helped in achieving the best performance.
In [10], C. Vishnu *et al.* proposed an approach using Convolutional Neural Networks (CNNs) for classification. They used their dataset of videos from the surveillance network at IIT Hyderabad campus and achieved good accuracy.

For automatic vehicle license number plate recognition, one of the most recent work was by B. V. Kakani *et al.* [16]. Their approach was based on improved Optical Character Recognition (OCR) using neural network. The steps involved were locating number plate, segmenting individual characters and then applying OCR on the characters.

III. PROPOSED WORK

Most of the existing systems for this problem statement use classifiers built on handcrafted features on the images/frames in video. Coming up with really good handcrafted features is a difficult task. This is why, deep Convolutional Neural Networks (CNNs) [14] have become popular in recent years for the job of image classification. CNNs learn rich feature representations from a broad range of images which often outperform handcrafted features and lead to more accurate and efficient image classification. Thus, implementation of system for this problem statement is done using CNN classifiers. One CNN classifier is used to classify between motorcyclist and non-motorcyclist and another CNN classifier is used to classify between helmet and non-helmet.

Building a CNN classifier from scratch requires huge amount of data and powerful hardware resources. Also, despite having both of these, the built CNN model might not perform really well due to problems in its architecture. So, transfer learning [13], [15] is used on top of one of the most popular CNN model, VGG-16 [12], that is pre-trained on the ImageNet [19] dataset. This has facilitated in obtaining high accuracy in classification.

Also, the system recognizes the number plates of motorcycles when the motorcycle has not worn helmet.
Our proposed system is divided into 7 steps which can be seen in Fig. 1.

Background subtraction and Object segmentation
Background subtraction [11] detects all the foreground moving objects like vehicles, pedestrians and discards all the stationary objects in the background like trees, road, etc. Background subtraction is done on the input CCTV footage video by calculating absolute difference between consecutive two frames of video. The output of background subtraction of two consecutive frames is a single binary image containing moving objects.

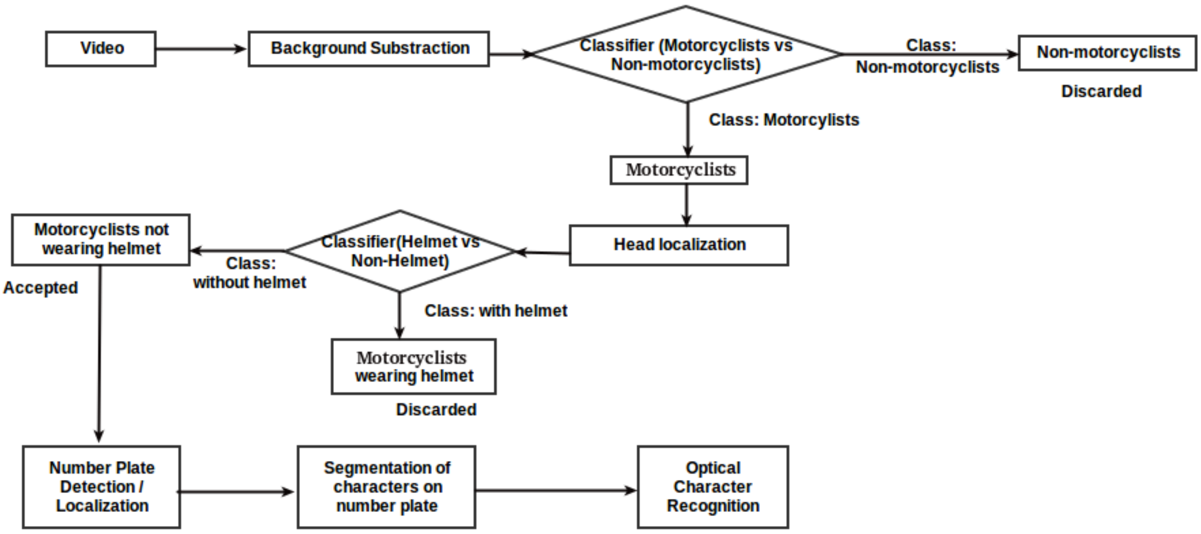

Fig.1. Flow chart of the proposed approach

To obtain appropriately segmented moving objects, Canny edge detection algorithm [18] is applied on each frame before calculating absolute difference between two consecutive frames. Canny edge detection algorithm detects wide range of edges in an image which help in object segmentation. Also, morphological operations are applied on the calculated absolute difference between two frames to remove noise and fill the gaps inside the white areas of the binary image to extract complete moving objects. After this, contours in the image are found out and individual moving objects are obtained.

To prevent the same vehicle getting detected more than once, the vehicles are extracted only when they reach a specific horizontal line. The lower boundary for the bounding contours is considered for this.

These individual moving objects are then fed to Motorcyclist vs Non-motorcyclist classifier. Segmented moving objects using result of background subtraction

This method used for background subtraction does not require image of background as input, making it independent of the video. Also, it is independent of various factors like quality of video and illumination.

Frame in original video | Result of background subtraction

Fig. 2. shows an example case of background subtraction and object segmentation.

Fig. 2. Background subtraction and Object segmentation

Motorcyclist vs Non-motorcyclist classifier
This classifier was built using transfer learning on our training dataset of motorcyclists and non-motorcyclists on top of VGG-16. VGG-16 is 16 layered CNN model on ImageNet dataset. For building this classifier model, only the convolutional layers of VGG-16 were taken. Then, a ReLU layer and a pooling layer were appended to it. Finally, a dropout followed by a softmax layer were appended. The convolutional layers were kept as it is and

only the added layers were trained on our training dataset. If a moving object fed to this classifier is classified as a motorcyclist, then it is forwarded for head localization; otherwise, it is discarded.

Head localization for detected motorcyclist

Once a moving object is classified as motorcyclist, image of the head portion is extracted by taking upper one-third portion of the original image. The extracted head portion is then fed to helmet vs non-helmet classifier.

Helmet vs Non-helmet classifier

This classifier was built similar to the Motorcyclist vs Non-Motorcyclist classifier. The layers added to VGG-16 were trained on our dataset of helmets and non-helmet objects.

If this classifier classifies the head portion image as helmet, then the original motorcyclist image is forwarded for number plate detection; otherwise the image is discarded.

Number plate detection (localization) for target motorcycle

Number plates have high contrast between foreground and background that is designed for humans so that they can read easily. This is a blessing for a computer vision problem.

Input motorcyclist image is first converted to grayscale. Then, it is thresh olded. After this, the binary image obtained is inverted. Now, the contours are found out. Minimum area rectangles are generated around the contours. At this point, not only the number plate is detected, but there might be few other parts of motorcycle detected too. These are filtered out based on their orientation, height, width, aspect ratio. After this step, many of the candidates get filtered out (in most cases, all except the number plate get filtered).

The remaining candidates are de-skewed, thresholded, eroded and contours are generated for each. Rectangles are then obtained for the contours. Image of number plate has numbers and letters on it which are separated by white colored area. Therefore, more rectangles get produced for a number plate image than other images. Thus, the image with number plate is successfully identified.

Fig. 3. shows an example of number plate localization. In this case, only two candidates remain after obtaining contours, generating rectangles and filtering. After thresholding these two images and finding rectangles, the number of rectangles produced for the number plate image are 11, whereas for the other there are 3. The one with more rectangles is the number plate image.

Original image After thresholding and inverting

After obtaining contours, generating rectangles and filtering

Fig. 3. Initial steps in number plate localization for target motorcycle

Segmentation of individual characters on detected number plate

Individual characters on number plate are segmented by thresholding the image for black color and finding contours. There characters are then sent for Optical Character Recognition.

Optical Character Recognition of segmented characters

Google's Tesseract Optical Character Recognition [17] is used to recognize the characters on the number plate and the output is stored, which can be used by Transport Office to penalize the concerned motorcyclists.

III. Experiment And Results

A. Tools and Platform Used

The system is developed in Python-2.7.12 using libraries such as OpenCV-3.3.0 for computer vision and image processing, Keras-2.1.2 with Tensorflow-1.4.1 backend for building CNN, scikit-image-0.13.1 for additional image processing tasks, scikit-learn-0.19.1 for machine learning and numpy-1.14.0 for multi-dimensional arrays, mathematical functions and linear algebra.

The experiments are performed on a machine with 64 bit Linux Ubuntu 16.04 Operating System running on it. The specifications of the system are 103.2 GB RAM, 4 Intel Xeon 2.40GHz processors and no GPU.

B. Dataset Used

Since there was no publicly available dataset for this problem statement at the time of commencement of the project, we requested the Road Traffic Division to provide us CCTV videos of traffic captured at road junctions. We used 2 hours video for training and 1 hour video for testing in our experiment. The training part contains 686 motorcycles and 694 non-motorcycles. The testing part contains 200 motorcycles and 430 non-motorcycles.

C. Results

In our experiment, motorcycle vs non-motorcycle classifier gave an accuracy of 99.68%, precision of 99.5% and recall of 99.5% on test dataset. Whereas, helmet vs non-helmet classifier gave 99.04% accuracy, 99.30% precision and 98.92% recall on test dataset. So, the overall accuracy for detection of motorcyclist without helmet came out to be 99.68% * 99.04% = 98.72%.

The accuracy of Tesseract OCR on our test images was 96.36%.

Table I shows performance metrics of each classifier on the test data. The metrics were calculated using following formulas:-

$$Accuracy = \frac{Number\ of\ samples\ correctly\ classified}{Total\ number\ of\ samples}$$

$$Precision = \frac{Number\ of\ +ve\ samples\ classified\ as\ +ve}{Total\ number\ of\ samples\ classified\ as\ +ve}$$

$$Recall = \frac{Number\ of\ +ve\ samples\ classified\ as\ +ve}{Total\ number\ of\ +ve\ samples}$$

TABLE I: PERFORMANCE OF EACH CLASSIFIER ON TEST DATA

Classifier	Performance (%)		
	Accuracy	*Precision*	*Recall*
Motorcycle vs non-motorcycle classifier	99.68	99.5	99.5
Helmet vs non-helmet classifier	99.04	99.30	98.92
Tesseract OCR	96.36	96.84	96.51

V. CONCLUSION

In the paper, we have described a framework for automatic detection of motorcycle riders without helmet from CCTV video and automatic retrieval of vehicle license number plate for such motorcyclists. The use of Convolutional Neural Networks (CNNs) and transfer learning has helped in achieving good accuracy for detection of motorcyclists not wearing helmets. The accuracy obtained was 98.72%. But, only detection of such motorcyclists is not sufficient for taking action against them. So, the system also recognizes the number plates of their motorcycles and stores them. The stored number plates can be then used by Transport Office to get information about the motorcyclists from their database of licensed vehicles. Concerned motorcyclists can then be penalized for breach of law.

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