



# AUTOMATIC DETECTION OF LICENSE PLATE NUMBER OF MOTORCYCLISTS WITHOUT HELMET

Anitha Moses V<sup>\*1</sup>, Bangalore Harika<sup>\*2</sup>, Brightlin Selvamary A<sup>\*3</sup>,  
Maddina Sreelekha<sup>\*4</sup>

<sup>\*1</sup>Professor, Department of CSE, Panimalar Engineering College, Chennai, TamilNadu, India

<sup>\*2</sup>Student, Department of CSE, Panimalar Engineering College, Chennai, TamilNadu, India

<sup>\*3</sup>Student, Department of CSE, Panimalar Engineering College, Chennai, TamilNadu, India

<sup>\*4</sup>Student, Department of CSE, Panimalar Engineering College, Chennai, TamilNadu, India

## ABSTRACT:

Helmet detection method is a combination of classification and cluster. Helmet detection is an important, yet challenging vision task. It is a critical part in many applications such as traffic surveillance. Our proposed method work is as follows, Pre-processing, Feature Extraction and classification. We demonstrate our proposed work by using surveillance traffic videos. Finally, our method will classify whether the person is wearing helmet or not. As far as the robustness and effectiveness are concerned, our method is better than the existing algorithms. The project presents license plate recognition system using connected component analysis and template matching model for accurate identification. Automatic license plate recognition (ALPR) is the extraction of vehicle license plate information from an image. This system model uses already captured images for this recognition process. First the recognition system starts with character identification based on number plate extraction, Splitting characters and template matching. ALPR as a real life application has to quickly and successfully process license plates under different environmental conditions.

## KEYWORDS:

Helmet Detection, License Plate Number Detection, Neural networks.

## INTRODUCTION:

Two-wheeler is a very popular mode of transportation in almost every country. However, there is a high risk involved because of less protection. To reduce the involved risk, it is highly desirable for bike-riders to use helmet. Observing the usefulness of helmet, Governments have made it a punishable offense to ride a bike without helmet and have adopted manual strategies to catch the violators. However, the existing video surveillance based methods are passive and require significant human assistance. In general, such systems are infeasible due to involvement of humans, whose efficiency decreases over long duration. Automation of this process is highly desirable for reliable and robust monitoring of these violations as well as it also significantly reduces the amount of human resources needed. Also, many countries are adopting systems involving surveillance cameras at public places. So, the solution for detecting violators using the existing infrastructure is also cost-effective. However, in order to adopt such automatic solutions certain challenges need to be addressed: 1) Real-time Implementation: Processing significant amount of information in a time constraint

manner is a challenging task. As such applications involve tasks like segmentation, feature extraction, classification and tracking, in which a significant amount of information need to be processed in short duration to achieve the goal of real-time implementation. 2) Occlusion: In real life scenarios, the dynamic objects usually occlude each other due to which object of interest may only be partially visible. Segmentation and classification become difficult for these partially visible objects. 3) Direction of Motion: 3-dimensional objects in general have different appearance from different angles. It is well known that accuracy of classifiers depends on features used which in turn depends on angle to some extent. A reasonable example is to consider appearance of a bikerider from front view and side view. 4) Temporal Changes in Conditions: Over time, there are many changes in environment conditions such as illumination, shadows, etc. There may be subtle or immediate changes which increase complexity of tasks like background modelling. 5) Quality of Video Feed: Generally, CCTV cameras capture low resolution video. Also, conditions such as low light, bad weather complicate it further. Due to such limitations, tasks such as segmentation, classification and tracking become even more difficult. As stated in, successful framework for surveillance application should have useful properties such as real-time performance, fine tuning, robust to sudden changes and predictive. Keeping these challenges and desired properties in mind, we propose a method for automatic detection of bike-riders without helmet using feed from existing security cameras, which works in real time.

## TYPES OF NEURAL NETWORKS:

There are three important types of neural networks that form the basis for most pre-trained models in deep learning:

1. Artificial Neural Networks (ANN)
2. Convolution Neural Networks (CNN)
3. Recurrent Neural Networks (RNN)

An artificial neural network (ANN) is the piece of a computing system designed to simulate the way the human brain analyzes and processes information. A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

## DEEP LEARNING TECHNOLOGY:

Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces. Most modern deep learning models are based on artificial neural networks, specifically convolutional neural networks (CNN)s, although they can also include propositional formulas or latent variables organized layer-wise in deep generative models such as the nodes in deep belief networks and deep Boltzmann machines. In deep learning, each level learns to transform its input data into a slightly more abstract and composite representation. In an image recognition application, the raw input may be a matrix of pixels; the first representational layer may abstract the pixels and encode edges; the second layer may compose and encode arrangements of edges; the third layer may encode a nose and eyes; and the fourth layer may recognize that the image contains a face. Importantly, a deep learning process can learn which features to optimally place in which level on its own. (Of course, this does not completely eliminate the need for hand-tuning; for example, varying numbers of layers and layer sizes can provide different degrees of abstraction.) The word "deep" in "deep learning" refers to the number of layers through which the data is transformed. More precisely, deep learning systems have a substantial credit assignment path (CAP) depth. The CAP is the chain of transformations from input to output. CAPs describe potentially causal connections between input and output. For a feedforward neural network, the depth of the CAPs is that of the network and is the number of hidden layers plus one (as the output layer is also parameterized). For recurrent neural networks, in which a signal may propagate through a layer more than once, the CAP depth is potentially unlimited. No universally agreed-upon threshold of depth divides shallow learning from deep learning, but most researchers agree that deep learning involves CAP depth higher than 2. CAP of depth 2 has been shown to be a universal approximator in the sense that it can emulate

any function. Beyond that, more layers do not add to the function approximator ability of the network. Deep models ( $CAP > 2$ ) are able to extract better features than shallow models and hence, extra layers help in learning the features effectively. Deep learning architectures can be constructed with a greedy layer-by-layer method. Deep learning helps to disentangle these abstractions and pick out which features improve performance. For supervised learning tasks, deep learning methods eliminate feature engineering, by translating the data into compact intermediate representations akin to principal components, and derive layered structures that remove redundancy in representation. Deep learning algorithms can be applied to unsupervised learning tasks. This is an important benefit because unlabeled data are more abundant than the labeled data. Examples of deep structures that can be trained in an unsupervised manner are neural history compressors and deep belief networks.

### **EXISTING SYSTEM:**

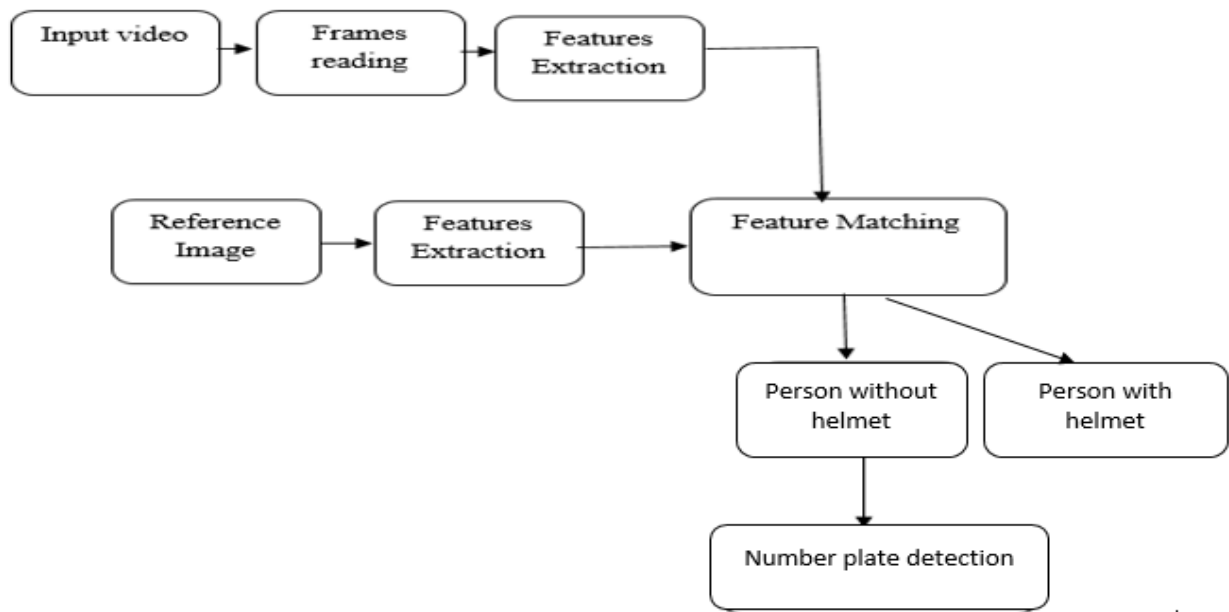
An object is separated from its background by using a segmentation technique called thresholding. This process involves, comparing each pixel value of the image (pixel intensity) to a specified threshold. Neighboring pixels are combined after thresholding into a ternary pattern. Computing a histogram of these ternary values will result in a large range, so the ternary pattern is split into two binary patterns. Histograms are concatenated to generate a descriptor double the size of LBP. Then object recognition is the technology used for finding and identifying objects in an image or video sequence. Then the license plate extraction is based on color and character features followed by texture based segmentation .

### **PROPOSED SYSTEM:**

The identification of objects in an image would probably start with image processing techniques such as noise removal, followed by (low-level) feature extraction to locate lines, regions and possibly areas with certain textures. Then an algorithm called feature descriptor is used which takes an image and outputs feature descriptors/feature vectors. Then a neural network called convolutional neural network (CNN) is used that has one or more convolutional layers and are used mainly for image processing, classification, segmentation and also for other auto correlated data. Then the license plate recognition system based on thresholding and Template matching using optical character recognition for automatic number identification is performed.

### **SYSTEM DESCRIPTION:**

This is a helmet and number plate detection system in which we get an input images and videos from traffic surveillance system which is given as a input to convolutional neural networks and process accurate output whether the person is wearing helmet or not .In the next process if the person is not wearing helmet then number plate detection will be done using convolutional neural networks and determines number plate characters of bike rider accurately and produces effective output .

**SYSTEM ARCHITECTURE:**

The modules involved in this project are

1. Input image
2. Image classification
3. CNN classifier
4. Final classification

The input video has been captured by using either ipcam or webcam, From this the bike is detected. This methods to detect the photo of motorcycle and driver from the image and then detect an area of the biker head before classify that this person is wearing a helmet or not. In this paper, we proposed to solve the biker and helmet detection problem from video surveillance data by using CNN models. After gathering images for our training dataset, we split our images into two groups, one for training data and another for test data to use in classification experiment. This experiment we test them with CNN models for image classification. All videos will be tested and calculated the accuracy of the biker with helmet and no helmet detection in the video. A CNN is a neural network with some convolutional layers (and some other layers). A convolutional layer has a number of filters that does convolutional operation. The last step, we compare the performance from two previous steps and make the conclusion. The accuracy of the experiments will show the performance of each technique in terms of image classification and image detection. Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task. Morphological operations are applied on segmented image for finding license plate number. Dilation and erosion process will be used to enhance (smoothing) the license plate region by removing the unwanted pixels from outside region of plate. After applying morphological process, we will get the foreground and background separated output. From this number plate is extracted.

**CONCLUSION:**

In this project, we propose a framework for detection of traffic rule violators who ride bike without using helmet. Proposed framework will also assist the traffic police for detecting such violators in odd environmental conditions viz; hot sun, etc. Experimental results demonstrate the accuracy of detection of bike-rider and detection of violators, respectively. Also, proposed framework automatically adapts to new scenarios if required, with slight tuning.

**REFERENCES:**

- [1] A. Adam, E. Rivlin, I. Shimshoni, and D. Reinitz, "Robust real-time unusual event detection using multiple fixed-location monitors," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 3, pp. 555–560, March 2008.
- [2] B. Duan, W. Liu, P. Fu, C. Yang, X. Wen, and H. Yuan, "Real-time onroad vehicle and motorcycle detection using a single camera," in *Procs. of the IEEE Int. Conf. on Industrial Technology (ICIT)*, pp. 1–6, 10-13 Feb 2009.
- [3] C.-C. Chiu, M.-Y. Ku, and H.-T. Chen, "Motorcycle detection and tracking system with occlusion segmentation," in *Int. Workshop on Image Analysis for Multimedia Interactive Services, Santorini*, pp. 32–32 June 2007.
- [4] W. Hu, T. Tan, L. Wang, and S. Maybank, "A survey on visual surveillance of object motion and behaviors," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 34, no. 3, pp. 334S–352, Aug 2004.
- [5] J. Chiverton, "Helmet presence classification with motorcycle detection and tracking," *Intelligent Transport systems (IET)*, vol. 6, no. 3, pp. 259–269, September 2012.
- [6] Z. Chen, T. Ellis, and S. Velastin, "Vehicle detection, tracking and classification in urban traffic," in *Procs. of the IEEE Int. Conf. on Intelligent Transportation Systems (ITS)*, Anchorage, AK pp. 951–956, Sept 2012.
- [7] R. Silva, K. Aires, T. Santos, K. Abdala, R. Veras, and A. Soares, "Automatic detection of motorcyclists without helmet," in *Computing Conf. (CLEI), XXXIX Latin American*, pp. 1–7, Oct 2013.
- [8] R. Rodrigues Veloso e Silva, K. Teixeira Aires, and R. De Melo Souza Veras, "Helmet detection on motorcyclists using image descriptors and classifiers," in *Procs. of the Graphics, Patterns and Images (SIBGRAPI)*, pp. 141–148, Aug 2014.
- [9] Z. Zivkovic, "Improved adaptive gaussian mixture model for background subtraction," in *Proc. of the Int. Conf. on Pattern Recognition (ICPR)*, vol. 2, pp. 28–31, Aug.23-26 2004.
- [10] C. Stauffer and W. Grimson, "Adaptive background mixture models for real-time tracking," in *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, vol. 2, 1999.