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A Simple Machine learning Method to Sense Vehicle Number Plate Driving without Helmet on Roads

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Abstract: *In order to recognize helmets, classification and clustering are used. The visual task of detecting a helmet's existence is crucial yet challenging. An application like traffic surveillance relies on this component. We suggest beginning with pre-processing, then moving on to feature extraction, and finally, classification. Photographs from traffic monitoring systems are used to illustrate our points. Finally, we'll know whether the individual is wearing a helmet or not thanks to our algorithm. When compared to other algorithms, ours is more robust and efficient. In this study, we trained a convolution neural network (CNN) model to identify license plates and helmets in a variety of images. This implementation of the system uses previously collected images for image recognition. The first stages of identification include extracting license plates, separating characters, and matching templates. The application's CNN model handling of license plates has to be quick and effective across a range of environmental conditions.*

I. INTRODUCTION

In almost every nation, the two-wheeler serves as the primary mode of transportation. Nevertheless, a substantial risk is there since adequate protections are not in place. Bike riders greatly reduce their exposure to road hazards when they wear helmets. It is now illegal to ride a bike without a helmet in many countries, and authorities are using random inspections and other manual means to catch offenders. This is all due to the fact that wearing a helmet is highly recommended by experts in the field. Present image-based surveillance systems, on the other hand, are quite manual and passive. Their efficacy deteriorates over time since these systems are dependent on people. Automating the process will make monitoring these infractions more robust and dependable while reducing the need for human resources. Also, more and more nations are using video systems to keep tabs on citizens in public spaces. So, it's possible to find criminals cheaply by using the infrastructure that already exists. Nevertheless, prior to implementing such automated solutions, certain obstacles must be overcome:

Launching in real-time Resolving a flood of data in a short period of time is challenging. Operations including as segmentation, feature extraction, classification, and tracking need lightning-fast processing of massive datasets to achieve real-time implementation.

In actuality, the moving parts often impede one another, making it so that the target is only partly visible. Classification and segmentation become more challenging when objects are only partly visible. From different angles, three-dimensional objects seem to be moving in different directions. As is well-known, the features used determine the accuracy of classifiers, which is influenced by the angle. Take, for example, a biker's front and side perspectives. Light, shadow, and other environmental factors change dramatically throughout time. For instance, whether the change is little or big, it might make background modeling more challenging.

II. LITERATURE REVIEW

An interconnected system of local monitors gathers basic data. whether a local monitor notices anything out of the ordinary with its current measurements, the data is utilized to determine whether anything out of the ordinary has happened. Our method allows for a large-scale monitoring system to fulfill many crucial needs. For example, it requires just a brief initial configuration before operating autonomously. Since it is not dependent on the motion of objects, it is more dependable than algorithms that require tracking. It usually takes a few minutes for the algorithm to become effective once enough low-level data showing regular activity have been gathered. Without fail, our algorithm is hard at work in the real world. It was tested in hectic real-world environments. We used a ground truth to test the detection and false-alarm rates in these conditions. using a single camera to detect motorbikes and cars in motion in real-time[1].

This research presents lane change assistants (LCAs) with real-time monocular vision for identifying and monitoring motorcycles and cars in the rear. In order to achieve resilience and accuracy, this approach utilizes numerous signals to detect and track many motorcycles and cars on the road. Each algorithm has been developed on a vision board with an integrated memory array processor (IMAP) for real-time multi-resolution technology. This system's quickness, accuracy, and durability were proven in several traffic conditions [2].

The study suggests a vision-based motorbike monitoring system that can identify and track motorcycles, and section 2.3 discusses occlusion segmentation for this purpose. The detection of occlusions in images may be accomplished using a segmentation method. We first identify the bikes' occlusion classes, and then we use the approach's visual length, visual width, and Pixel Ratio to segment the motorcycles from each occlusive class. The purpose of using the helmet detection or search technique is to guarantee the rider's and motorcycle's safety. Experimental results using genuine road circumstances show that the technique is resilient, accurate, and sensitive to time [3].

The use of motorcycle detection and tracking allows us to categorize riders based on whether or not they are wearing helmets[4].

Motorcyclists' safety depends on their wearing helmets, yet mandating their usage is a tedious and time-consuming process. An automated system for distinguishing between motorcyclists wearing helmets and those who do not has been developed and put through its paces. Training support vector machines on histograms obtained from image data of motorcycle riders' heads is done using static photos and individual image frames. Background removal trained on the classifier automatically removes motorcyclists from image data. The cyclists' heads are categorized using the trained classifier. The tracks that each motorcyclist makes are unique collections of zones marked with timestamps. Overall track classification is achieved by averaging the individual classifier outputs. According to the test findings, classifiers can correctly determine whether bikers are wearing helmets using just static images. The testing conducted by the tracking system confirms the accuracy and utility of the categorization method [5] [6].

Figure 2: Snapshots of helmets captured at noon and dusk.

An approach to vehicle detection, tracking, and classification via the use of roadside CCTV is introduced in this work. The system counts and classifies all vehicles, including cars, vans, buses, and motorbikes (including bicycles) [7]. New background Gaussian Mixture Model (GMM) and shadow removal approach were used to handle the sudden shifts in light and camera shaking. A majority vote across many frames may be used to classify the foreground blob using a level set technique and a Kalman filter. A large number of tests have been conducted utilizing real-world data to evaluate the system's performance. The most effective method involves training an SVM (Support Vector Machine) using a silhouette of the car and intensity-based pyramid HOG features that are retrieved after background removal. The goal is to detect foreground blobs using the majority vote.

III. IMPLEMENTATION

One segmentation method that may be used to separate an item from its surroundings is thresholding. This procedure involves comparing the intensity of each pixel to a preset threshold. A ternary pattern is formed by joining neighboring pixels after thresholding. Since ternary values may take on many forms in a histogram, the pattern is split into two binary versions. A description that is twice as big as LBP is constructed by joining histograms. The process of finding and identifying objects in a picture or series of images is known as object recognition. After extracting the license plate using its color and character components, texture-based segmentation is applied. It is possible to use noise reduction and other low-level image processing methods first, and then extract features like lines, regions, and maybe even places with particular textures.

Afterwards, it extracts feature descriptors or feature vectors from an image using a technique called a feature descriptor. The next step is to use a convolution neural network (CNN). These networks typically include one or more convolution layers and are applied for tasks such as auto-correlated data processing, image processing, classification, and segmentation. The next step is to develop a system that can recognize license plates using optical character recognition and thresholding/template matching.

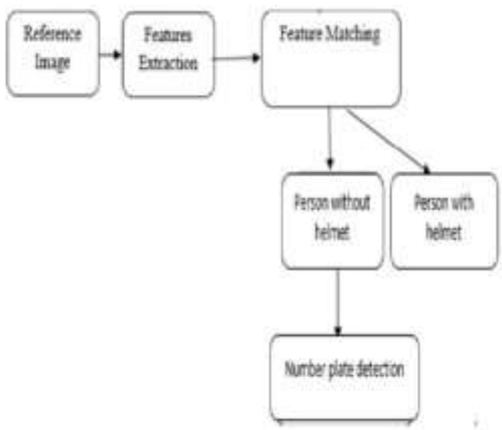

Fig.3: System architecture

uses images captured by a traffic surveillance system and put into convolution neural networks to determine whether a rider is wearing a helmet and, if so, what license plate it is. Next, we'll utilize convolution neural networks to accurately and efficiently detect the bike rider's license plate characters if they aren't wearing a helmet.

The modules involved in this project are

1. Upload image
2. Detect motor bike & person
3. Detect helmet

It is possible to identify the bike in the picture using either an ipcam or a webcam. This method seeks for images of motorbikes and their riders before classifying them according to the presence or absence of helmets. In this research, we used convolution neural network (CNN) models to the problem of recognizing helmeted bicyclists in surveillance footage. After we had gathered enough images to form our training dataset, we split them in half and placed one side aside to use for training and the other for testing. Convolution neural network (CNN) models were used to categorize photos in this investigation. After reviewing all of the photos, we will make sure that we can accurately determine the rider in the shot, helmet or no helmet. Multiple layers comprise convolution neural networks (CNNs) and similar systems. Multiple filters inside a convolution layer execute the convolution process. The last step is to compare the outcomes of the previous steps. Experimental accuracy will be used to assess the performance of picture detection and image classification. This technique of working with photographs at their most basic level is called "image pre-processing." With entropy as a measure of data content, these operations really make things worse. Preprocessing may enhance an image's quality by enhancing certain areas crucial for further processing and analysis or by eliminating undesired artifacts. Morphological approaches are used to a segmented picture in order to find the license plate number. By removing any unnecessary pixels from the outside region of the license plate, the dilation and erosion approach will enhance (smooth) the plate's overall area. Following morphological processing, we will get the ability to distinguish between the foreground and background. Someone has stolen this license plate.

IV. ALGORITHM

CNN:

It is assumed that the reader has some background knowledge with neural networks. In the field of Machine Learning, Artificial Neural Networks shine. Applications of artificial neural networks include image, audio, and word categorization, among others. Picture categorization makes use of both LSTM and Convolution Neural Networks, whereas word sequence prediction makes use of both Recurrent and Convolution Neural Networks. The Convolution Neural Network will be introduced after we review the fundamentals of neural networks. The input, output, and hidden layers make up a normal neural network. Data layers that need to be input: At its core, this is the data-feeding layer of our model. This layer has the same amount of neurons as our data, or the number of pixels in a picture. After the input layer, the hidden layer receives the data. The number of hidden layers will depend on the model and the amount of the data. Each buried layer's neuron count grows in proportion to the number of features. The output of a nonlinear network is produced by taking the output of one layer and multiplying it by the learnable biases and weights of that layer. Then, an activation function is applied to the resultant matrix.

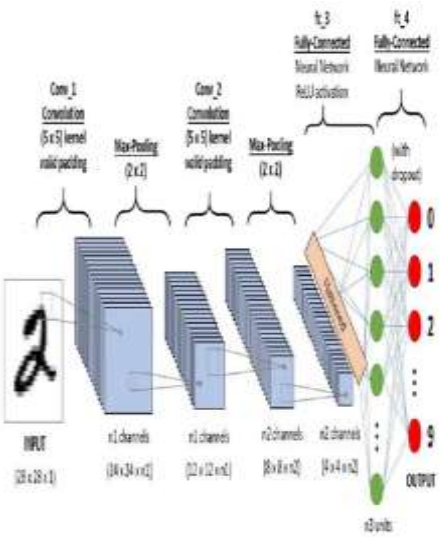

Fig.4: CNN architecture

Step by Step Procedure:

Step 1: Choose a Dataset. ...

Step 2: Prepare Dataset for Training. ...

Step 3: Create Training Data. ...

Step 4: Shuffle the Dataset. ...

Step 5: Assigning Labels and Features. ...

Step 6: Normalizing X and converting labels to categorical data. ...

Step 7: Split X and Y for use in CNN.

V. EXPERIMENTAL RESULTS

In images where helmets are absent, the app will recognize the license plate; in images where helmets are present, the app will not recognize the plate. Because there aren't enough pictures to train the CNN model, our app can only identify helmets in 25 out of 100.

Fig.5: Home screen.

In above screen click on ‘Upload Image’ button to upload image

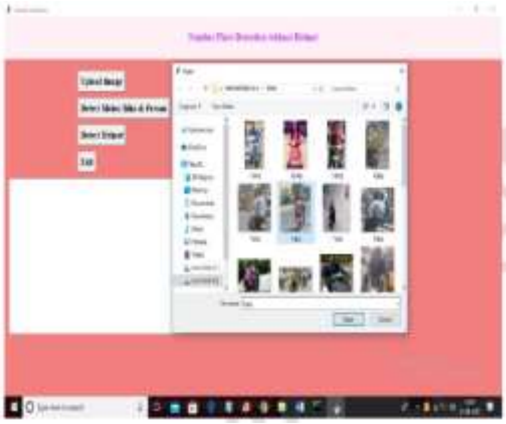

Fig.6: Image upload

To check for the presence of a motorbike rider in a picture, for instance, choose the file "6.jpg," click "Open," and then choose "Detect Motor Bike & Person."

Figure 7: Locate motorcycle and pedestrian

Pressing the "Detect Helmet" button on the aforementioned screen will provide the following output whenever a bicyclist is detected.

Figure 8: Helmet Detection

The program finds the license plate number and shows it as 'AP13Q 8815' in the text field, but the helmet isn't shown in the screenshot above.

CONCLUSION

Our objective is to develop a system that can detect lawbreakers who are riding bicycles without protective headgear. In extreme circumstances, such a scorching heat, the suggested framework would also aid the traffic police in identifying these offenders. The experimental findings demonstrated that both the identification of bike riders and the detection of infractions were accurate. The suggested architecture is quite flexible and may be adjusted to suit any new circumstance.

Section 7: Looking Ahead
In the future, this idea will be expanded upon using video frames. Even without a helmet, we can clearly identify the license plate in videos.

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 ystems (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 Process. 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.