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TRACKING LICENSE PLATE NUMBER AND CLASSIFICATION OF NON-HELMET RIDERS USING NEURAL NETWORKS

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ABSTRACT:

Identifying helmets is done by categorization and grouping. The visual task of identifying a helmet is crucial yet challenging. This is a crucial component for many uses, especially in areas like traffic monitoring. It is our intention to first do pre-processing, and then feature extraction, and finally classification. Images from traffic cameras are used to illustrate our points. At the end of the day, our algorithm will be able to tell if the subject is wearing a helmet. When compared to other algorithms, ours is more robust and efficient. As part of this study, a convolutional neural network (CNN) model was developed to identify HELMETS and vehicle registration numbers in photographs. In order to accomplish its goal of image recognition, this version of the system takes use of previously collected images. In order to begin the recognition process, data must be extracted from the license plate, characters must be divided, and a template must be matched. The CNN model must let the application to quickly and accurately process license plates in different settings.

INTRODUCTION

The two-wheeled vehicle is widely used as a mode of transportation across the world. But since there aren't any controls in place, it's also very risky. Bicycle riders may greatly reduce their exposure to road hazards by using protective headgear. Governments have declared it illegal to ride a bike without a helmet due to the dangers of not wearing one, and they have developed random inspections and other manual means of detection. In contrast, the active nature of human interaction is central to the current image-based surveillance systems. These systems lose effectiveness over time since they are dependent on human input. The monitoring of these infractions will be more dependable and robust, and less human resources will be needed, if it is automated. In addition, an increasing number of nations now deploy camera networks to keep tabs on citizens in crowded public spaces. That means it's possible to use existing infrastructure to find criminals for cheap. While such automated solutions hold great promise, they must first overcome a number of obstacles. Real-time implementation managing a lot of data in a limited period of time is challenging. Operations like segmentation, feature extraction, classification, and tracking that aim at real-time implementation need the efficient processing of massive volumes of data. In most real-world situations, the item of interest is only partly visible because moving things obscure it. It's harder to categorize and divide items into groups when just a portion of them is visible. By their very nature, three-dimensional things seem like they're moving in different directions depending on the viewpoint used to examine them. It is well-known that the characteristics used, which in turn rely on the angle, greatly affect the classifier's accuracy. As an example, think of a biker seen from the front and the side.
Lighting, shadows, and other environmental factors are subject to a wide range of changes throughout time. Changes in the environment, both major and minor, may increase the difficulty of tasks like background modeling. CCTV cameras often acquire low-resolution pictures via their image feeds. Things like low visibility and bad weather make this a lot harder to do. Tasks like segmentation, classification, and tracking become more challenging as more stringent criteria are used. Real-time performance, fine-grained tuning, resilience to quick changes, and the ability to predict the future are all essential components of effective surveillance architecture. Due to these restrictions and required features, we built a system to identify bikers without helmets in real-time using surveillance camera video.

2. LITERATURE REVIEW

2.1 Robust real-time unusual event detection using multiple fixed-location monitors:

In this article, we show how to use a novel method to spot certain types of abnormal occurrences. A system of regional sensors collects basic metrics. If a nearby sensor reports something out of the ordinary, that information will be used to confirm or refute the possibility of an anomalous occurrence. Our method ensures that a massive monitoring network can fulfill crucial needs. For example, after a brief period of configuration, it may function alone. Since it doesn't rely on the motion of objects, it is more dependable than tracking-based algorithms. In most cases, the method becomes effective within a few minutes, when a significant number of low-level observations indicating regular activity have been acquired. Our method is operational in all conceivable global scenarios. It was tested in hectic environments that mimicked real life. For these cases, a ground truth was used to calculate the detection and false-alarm rates.

Using a solitary camera for on-the-road vehicle identification this research presents a real-time monocular vision system for lane change aides (LCA) that can recognize and track vehicles in the rear view mirror. In this study, various signals are used to identify and track individual vehicles and motorcycles, making for a robust and precise solution. Algorithms for real-time, multi-resolution imaging have been developed using a vision board that use a parallel IMAP (integrated memory array processor). Several traffic scenarios were used to prove the system's accuracy, robustness, and responsiveness.

Motorcycle detection and tracking with occlusion segmentation 2.3:

The study presented here proposes a vision-based motorbike surveillance system that can identify and track motorcycles. An image occlusion detection segmentation method exists. Visual length, visual breadth, and Pixel Ratio are used to identify motorcycle occlusion classes, and then bikes within each occlusion class are segmented. The detection or search technique for helmets is used to ensure the safety of the motorbike and its rider. Experiments using genuine road circumstances have shown the approach to be resilient, accurate, and temporally sensitive.

Here, we provide a brief overview of methods for observing the motion and actions of objects using only sight. Currently, visual surveillance in dynamic situations, especially for people and vehicles, is one of the most active areas of research in computer vision. Access control in limited areas, remote person identification, traffic congestion analysis, abnormal behavior detection, interactive monitoring with many cameras, and many more uses are possible with this technology. Modeling the environment, detecting motion, categorizing moving objects, monitoring and analyzing behavior, identifying people, and fusing data from several cameras are all part of the processing architecture designed for visual surveillance in dynamic settings. Current developments and the underlying techniques are explored together with each individual step of the process. Finally, we consider future research opportunities, such as occlusion management, two- and three-dimensional tracking, a motion analysis/biometric combination, anomaly detection/behavior prediction, content-based image retrieval, behavior understanding/natural language description, and remote surveillance.

The identification and monitoring of motorcycles allows us to identify whether or not a rider is wearing a helmet. Helmets are essential for the safety of motorcyclists, but enforcing their usage is time-consuming and difficult. The automated identification and location of helmeted and undeleted motorcyclists has been described and tested. Histograms derived from motorcycle riders' heads are used to train support vector machines using still images and frames from the corresponding data. Classifier-trained background subtraction is used to automatically extract motorcycle riders from image data. The classified riders' heads are based on the trained classifier. Every motorcyclist blazes their own trail, which consists of a series of time-stamped segments. The tracks are collectively labeled based on an average of the results from the separate classifiers. Test results show that classifiers can reliably determine, from static images, whether or not a rider is wearing a helmet. The categorization method is shown effective and accurate by the testing of the tracking system.

Fig.2: Photographs of helmets taken at midday (left) and at dusk (right).

2.6 Vehicle detection, tracking and classification in urban traffic

This study introduces an approach to employing roadside CCTV to identify, track, and categorize cars. The system can count and classify a wide variety of vehicles, including cars, vans, buses, motorbikes, and even bicycles. To combat the jarring shifts in lighting and camera motion, an updated background Gaussian Mixture Model (GMM) and technique for eliminating shadows were used. The background blob may be labeled using a majority vote based on a number of frames using a Kalman filter and a level set technique. Many experiments have been conducted with real-world data to evaluate the effectiveness of the system. The most accurate results are achieved by training an SVM (Support Vector Machine) using intensity-based pyramid HOG features retrieved from the foreground after the background has been subtracted from the image. **3.**

IMPLEMENTATION

As a segmentation method, thresholding helps to separate a target feature from its background. In this procedure, the intensity of each pixel is compared to a standard. Thresholding is followed by the joining of neighboring pixels to create a ternary pattern. Since a histogram can contain a wide variety of ternary values, the ternary pattern is broken down into two binary ones. Histograms are linked together to form a description that is twice as big as LBP. Object recognition refers to the methods used to detect and label objects in a still picture or video sequence. License plates are extracted using color and character components, then segmented using texture. Extraction of features like lines, regions, and sometimes even areas with distinct textures may follow initial low-level image processing approaches like noise reduction.From then, it employs a feature descriptor technique to generate feature descriptors/feature vectors. Next, a convolutional neural network (CNN) is utilized, which is often applied in the processing of images, as well as classification, segmentation, and other forms of auto-correlated data. It is possible to create a license plate recognition system using OCR and thresholding/template matching.

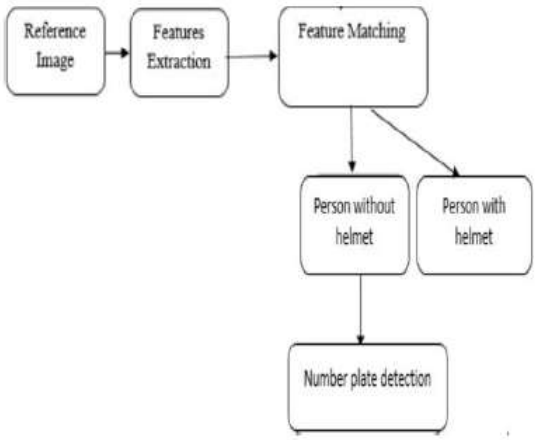

Fig.3: System architecture

Images captured by a traffic surveillance system are input into convolutional neural networks, which can then determine whether or not a person is wearing a helmet and read their license plate. If the biker isn't protecting their head with a helmet, convolutional neural networks will read the license plate and provide useful results.

The modules involved in this project are

1. Upload image

2. Detect motor bike & person

3. Detect helmet

The picture may be decoded using either an ipcam or a webcam to reveal the bike's location. This method recognizes a motorcycle and its rider in an image before classifying whether or not the subject is wearing a helmet. In this research, we employed convolutional neural network (CNN) models to detect motorcyclists and their helmets in surveillance footage. After amassing enough images for our training dataset, we split them up into two groups: those that would be used for actual training, and those that would be used for actual testing. CNN models were used to categorize photos for this investigation. All photographs will be scrutinized and analyzed to ensure the accuracy of detecting the biker with and without a helmet in the image. CNNs, and similar convolutional neural networks, are multi-layered structures. Multiple filters in a convolutional layer perform the convolutional operation. We reach a conclusion by comparing the outcomes of previous steps. The effectiveness of picture classification and detection will be measured by the results of these experiments. Performing tasks on images at the most primitive level of abstraction is known as "image pre-processing." If information is measured in terms of entropy, then these processes will result in less entropy. Preprocessing may enhance an image's quality by eliminating distracting artifacts or enhancing certain features necessary for further processing and analysis. Using morphological operations on a segmented picture, we may locate the license plate number. Dilation and erosion will be used to smooth up the license plate area by removing excess pixels around the plate's perimeter. After morphological processing, we'll be able to tell what's in the front and what's in the background. This license plate was stolen.

4. ALGORITHM

CNN:

The reader should have some background knowledge of neural networks. Machine learning is a strong suit for artificial neural networks. Artificial neural networks are used for a wide variety of classification tasks, including those involving images, audio, and words. Images may be classified using LSTM and Convolution Neural Networks, while word sequences can be predicted using Recurrent Neural Networks and Convolution Neural Networks. Before we get into the Convolution Neural Network, let's review the fundamentals of neural networks. Three layers make up a typical Neural Network, including the input layer, the output layer, and the hidden layer. Multiple levels of information entry: This is the layer where the data is stored and used by the model. In this layer, the number of neurons equals the number of data points (or image pixels, in this case). The hidden layer receives data from the input layer. Multiple hidden levels may be present, though this will depend on the complexity of our model and the amount of data we have. The number of neurons in each hidden layer grows in proportion to the number of features. The output of a nonlinear network is calculated by applying an activation function to a matrix obtained by multiplying the output of the preceding layer by the layer's tunable weights and biases.

In the output layer, the output of each class is converted into a probability score for each class using a logistic function like sigmoid or softmax. Next, the error can be computed using an error function, such as cross-entropy or square loss error, applied to the model's output. We call this iteration "feed forward." The derivatives are then used to go backwards through the process and arrive at the original model. Data loss may be minimized with the use of backpropagation.

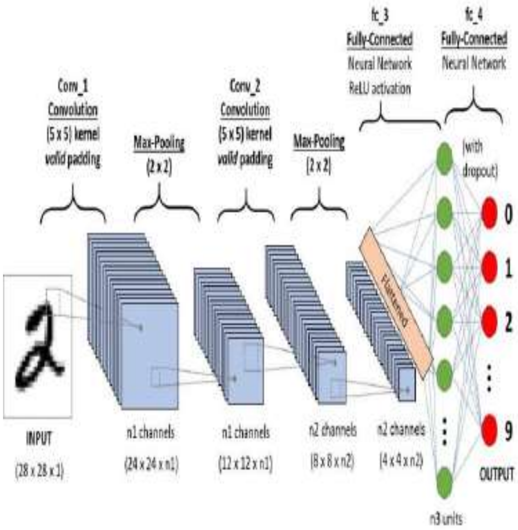

Fig.4: CNN architecture

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.

5. EXPERIMENTAL RESULTS

If a helmet is not visible in the photograph, the app will detect the license plate; otherwise, it will ignore the image. Due to a lack of training data, our program can only identify a helmet in 25 out of an expected 10,000.

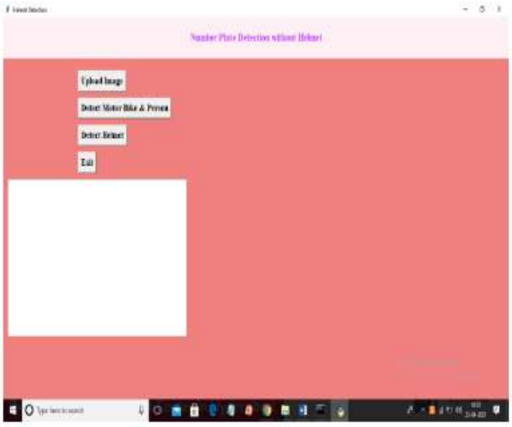

Fig.5: Home screen.

In above screen click on 'Upload Image' button to upload image

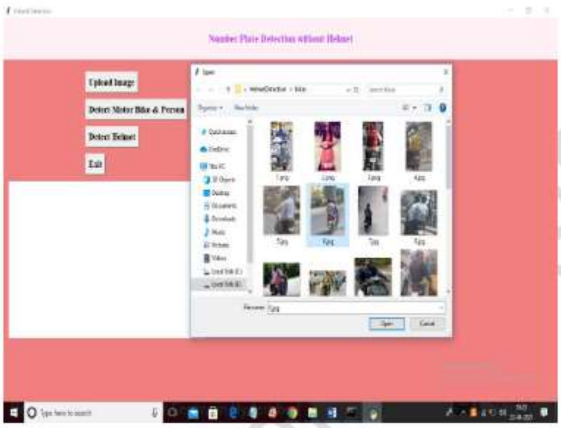

Fig.6: Upload image

Choose and upload the file "6.jpg," then click "Open," and last choose "Detect Motor Bike & Person" to check whether the picture contains a person on a motorbike, for instance.

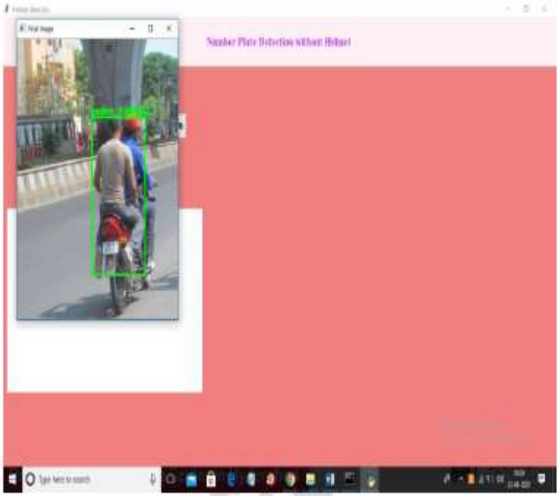

Fig.7: Detect motor bike & person

The following is the result of pressing the 'Detect Helmet' button on the preceding screen if a cyclist is detected.

Fig.8: Detect helmet

Above, we can see that the application does not recognize the helmet, but it does recognize the license plate number and display it as "AP13Q 8815" in the text box.

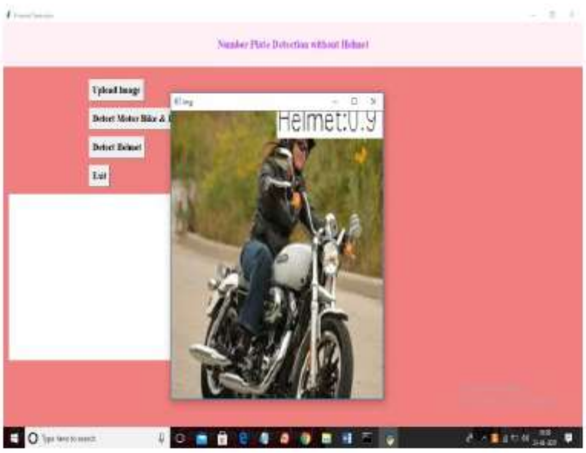

Fig.9: Another detection screen

App discovered a helmet with a matching score of 0.90 percent on the above screen.

6. CONCLUSION

Our mission is to find a way to track down lawbreakers on two wheels who aren't wearing helmets. The suggested framework would also aid the traffic police in identifying such offenders under extreme weather conditions like the scorching heat. The results of the experiments confirmed the efficacy of both the bike rider identification and the infraction detection. The suggested design is flexible enough to adjust to any unanticipated conditions.

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