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TRAFFIC SIGN DETECTION, TRIPLE RIDING AND HELMET DETECTION

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Abstract: The number of accidents caused by reckless drivers who flout traffic laws has been steadily increasing in the modern world. As the number of vehicles on the road increases, so do the number of traffic accidents.

The use of synthesized training data generated from images of road traffic signs allows us to solve traffic sign detection issues and reduce traffic law violations by identifying incidents such as triple riding, helmet-free driving, and accidents that vary by nation and region.

Using a convolution neural network (CNN) and this data, it is feasible to generate a database of synthetic photos that may be used to detect traffic signals, triple riding, helmet-free drivers, and accidents in a variety of view illumination settings.

This ensures fewer accidents and allows the driver to focus on driving rather than reading every traffic sign. It also helps to identify occurrences such as triple riding, not wearing a helmet, and accidents.

Keywords: triple riding, convolution neural network (CNN), synthesised training data, traffic sign recognition, accident rateOverview (heading 1)).

Recognition of road signs has evolved as a significant and difficult field in both academics and industry. One of the primary applications for this technology will be in the burgeoning field of artificial intelligence (AI), which seeks to grasp its surroundings. It is also an essential part of advanced driver assistance systems (ADAS). In general, the identification process provides drivers with a clear visual definition of the surroundings and road limits that each traffic sign may express using a range of forms, colors, and images. This allows the driver to foresee probable obstacles and prepare for them. It is not expected that road signs will be very visible to motorists; there may be some confusion between them, and only a small percentage of vehicles will be able to recognize specific indicators. This could lead to misunderstandings and increase the chance of accidents. It could be dangerous if you are unsure about spotting warning signs. Nonetheless, there are some cases where road signs become completely distorted owing to numerous environmental variables, making it difficult for both humans and machines to interpret them. The classification process considers the observer's point of view, which includes characteristics such as the sign's lighting, potential obstructions that may obscure particular elements of the sign, the time difference between twilight and dawn, color fading, and motion blur.

Almost every country has a pretty ubiquitous kind of transportation: two-wheelers. However, because there is minimal protection, the danger increases. It is highly recommended that cyclists use helmets in order to mitigate the associated risks. Motorcycles are the primary catalyst for traffic accidents. Although irresponsible and negligent driving is the primary cause of road accidents, head injuries are responsible for the majority of deaths. Research indicates that the utilization of a helmet can reduce the fatality rate of accidents by 30-40%. Over 33% of those who died in car accidents could have lived if they had taken appropriate action. A significant proportion of cyclists have been engaged in traffic collisions while neglecting to wear protective helmets. Additionally, it is necessary for it to adhere to the Bureau of Indian

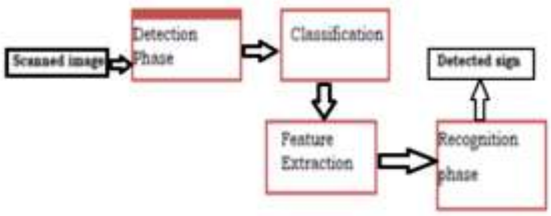
Standards and possess the ISI seal. Regrettably, it seems that these restrictions are not adhered to by anyone, particularly pillion riders. In today's period of human development, video surveillance-based systems have become an indispensable instrument for monitoring any illegal or unethical behavior. There are currently approaches for detecting the presence of a helmet utilizing specific sensors embedded into the motorcycle's ergonomics. However, it is not realistic to persuade every user to equip their existing bikes with sensors. Furthermore, there are concerns concerning the reliability and precision of these sensors. Furthermore, the computing costs of video processing systems are relatively high. The exorbitant expense of the technology used to build the system made it unfeasible financially.

I. LITTERATURE REVIEW

DEEP LEARNING BASED DIFFERENT APPROACHES OR METHODS

The introduction of deep learning techniques in computer vision has enabled the development of the most powerful learning classification systems available, supported by massive datasets. This has made it easier to detect distinguishing class characteristics. One of these techniques is known as convolutional neural networks. The fundamental distinction between CNNs and prior techniques, despite the inclusion of kernel filters, is the use of Max Pooling layers rather than sub-sampling. The chosen shape combines Max Pooling and convolution layers, resulting in a single pixel reduction in the images' downsampled dimensions. The final results are organized in a way that balances the outputs produced by each neural network in the system. The digit recognition experiment illustrates how every network output is balanced using the same idea. The technique improves its accuracy on the test dataset by averaging many CNNs. It resolves the concerns that arose in numerous circumstances. Compared to previous ways, this strategy delivered significantly better results. The recognition level is fairly accurate. [1].

MODEL FOR TRAFFIC SIGN DETECTION



DETECTION PHASE

At this moment, each image captured by the car's installed camera is processed before being routed to the identification stage. The preprocessing stage includes the procedures for converting an RGB image to HSV. Because the HSV shading space outperforms the normal RGB shading space, it is used. The fundamental reason Hue Saturation Value is used in image identification is that it closely approximates what the human eye sees when compared to an RGB image. The RGB picture uses three primary hues to discern colors. Changes in border light have less of an impact on the HSV picture. Furthermore, the HSV image's histogram can be adjusted to automatically shift the contrast. After converting the RGB image to HSV, the following step is to identify the things based on their color saturation levels and shapes before determining which object to label as a traffic sign.

VALIDATION OF ROAD SIGN

After locating the box, the following step is to verify the sign. Whatever the case, the image we're working with has been reversed, which means that the outer triangle, which was originally white, has been transformed to black, and the inner triangle, which was originally black, has been converted to white. Now, a triangle that touches the boundary but neither the boundary box or the outside triangle is considered a sign. If the triangle on the border is white, it is not considered a sign. After being downscaled to 32 by 32, the image is transferred to the next stage. A green circle has been placed around the identified traffic sign to indicate its location. We may now use OpenCV, as we have highlighted the detected sign in green.

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RECOGNITION PHASE

Signs must be categorized immediately upon detection. TensorFlow, a machine learning framework built by Google, is utilized for constructing convolutional neural networks. To commence this phase, the initial step involves preprocessing the images obtained from earlier iterations. The testing and training conducted by CNN are considered to be the most crucial elements of the recognition phase. We utilized the "German Traffic Sign Benchmark and Belgium Traffic Signs" dataset for the purposes of testing and training. Due to possessing all the functions and characteristics of a typical brain, CNN is commonly referred to as the brain. Every individual neuron gets incoming information and transmits it to the subsequent cell. The input layer is the initial layer in a series of CNN layers, whereas the output layer is the last layer. There exists an obscured intermediary layer positioned between the initial and final layers. This method utilizes a total of six Convolutional Neural Network (CNN) layers. A completely integrated hidden layer prevents the occurrence of overfitting in the midsection. The model utilized in this case was constructed using Keras, with a "sequential stack" implemented on top of TensorFlow. Every layer includes a "Rectified Linear Unit activation." Relu serves as the principal activation function in neural networks. The output of the sixth convolution layer, which employs a pooling operation to flatten the output, is then passed to the fully connected layer. The flattened output is subjected to the last layer, which applies softmax activation. In order to enhance processing efficiency, a max pooling layer is positioned immediately following the initial two layers. By employing a collection or group of three similar CNNs, we can attain enhanced outcomes. Employing many Convolutional Neural Networks (CNNs) instead of a single one will yield more precise outcomes. One must define elements such as the optimizer, loss function, and metric. Instead of using percentages, the loss is measured using a numerical scale from zero to one. The optimizer employs the "Stochastic Gradient Descent with Nesterov momentum" technique. Utilizing epochs in the training process leads to enhanced prediction accuracy. The current technology incorporates a text-to-speech feature to assist drivers in preventing accidents and comprehending traffic signs with greater ease. This module is capable of identifying traffic signs and producing audio output.

CNN-BASED AUTOMATED HELMET DETECTION FOR MANY MOTORCYCLE RIDERS

Any smart traffic system must have automated detection of people who break traffic rules. Motorcycles are one of the most common modes of transportation in India, since all major cities have high population densities. The majority of motorcycle accidents can be avoided by wearing a helmet, which reduces the rider's risk of serious head and brain injuries. Most traffic and safety laws can now be broken down by studying traffic film captured by security cameras. This paper proposes a method for recognizing individual or group motorcycle riders who do not wear helmets. The proposed methodology initially identifies motorcycle riders using the YOLOv3 model, A progressive iteration of the YOLO model, which is considered the most sophisticated technique for object recognition. A Convolutional Neural Network (CNN)-based architecture was implemented in the second stage to detect motorbike riders who are wearing helmets. The suggested model demonstrates good results when evaluating traffic logs, in comparison to existing CNN-based approaches.

The proposed method involves analyzing traffic surveillance footage to identify individuals or groups of riders who, in essence, are all motorcycle riders who do not wear helmets. Motorcycle riders were recognized using the initial YOLOv3 model. Next, the proposed lightweight convolutional neural network detects whether or not all motorcycle riders wear helmets. With an accuracy of 96.23%, the proposed model excels at helmet identification in a variety of circumstances. Results from the proposed approach for detecting motorcycle riders' helmets 2000 2500 3000 3500 4000 4500 500 1000 1500 2500 2000 2500 Repetition Precision AP = Average Precision. The average precision for helmet detection using iteration-based techniques is 0.4 0.5 0.6 0.7 0.8 0.9. It can be expanded in the future to recognize more complex circumstances with several riders, including children. This approach can also be used to detect helmetless motorbike riders in more complex adverse weather conditions.

WEARING A SAFETY HELMET AND USING IMAGE PROCESSING FOR DETECTION

Ensuring the identification of safety helmet usage is of utmost importance in power substations. This study presents a novel and effective method for detecting safety helmets using image processing and machine learning techniques. Initially, a stationary security camera installed at a power substation use the ViBe backdrop modeling technique to identify and track any objects in motion. Once the motion zone of interest is acquired, the Histogram of Oriented Gradient (HOG) feature is employed to describe the characteristics of the individual therein. The Support Vector Machine (SVM) is subsequently trained to categorize pedestrians by utilizing the outcomes of HOG feature extraction. Ultimately, the utilization of color feature recognition will be implemented to identify the safety helmets. Empirical evidence has unequivocally shown that our suggested approach is both precise and effective.This work examines a novel and pragmatic method for real-time detection of safety helmet usage in power substations, irrespective of whether individuals are really wearing safety helmets. Power substation surveillance systems utilize machine learning and image processing methodologies. The ViBe background modelling method was used to segment the moving items captured by the monitoring camera. This method has the ability to effectively sort through a substantial quantity of stationary objects. The process of identifying humans in each frame involved the utilization of a support vector machine (SVM) classifier for training and the extraction of oriented gradient (HOG) features. Ultimately, we utilized color characteristics to ascertain the specific situations in which a protective helmet was worn.

CAPTURING PHOTO :

A Raspberry Pi-connected camera captures the video stream of the location under observation.

Vehicles and people can be recognized in video feeds using computer vision techniques such as Har Cascades or YOLO (You Only Look Once).

TRIPLE RIDING DETECTION:

Once people are identified, a triple riding identification method can be utilized to determine whether more than two people are riding a motorcycle. This could include approaches such as finding and situating the riders on the bike and comparing that data to a threshold.

II. CONCLUSION

This chapter methodically explains the traffic sign detecting block diagram, which is an important aspect of the overall system's development. This chapter provided a deep understanding of the underlying mechanisms by closely exploring the many stages of system development. The primary focus has been on a thorough investigation of each block in the diagram, which has shown their distinct purposes and significance. This inquiry contributes to a better knowledge of the system's design while also providing insights into the technical subtleties of traffic sign detection. The chapter expands our understanding of the technological foundations of effective traffic sign identification by emphasizing the importance of each block. Simply put, it is a wonderful resource for anyone seeking technical knowledge as well as a deeper understanding of the issues connected with developing advanced traffic management and road safety systems.

III. FUTURE WORK

While there is room for enhancement, the model suggested in this investigation moves us closer to the desired Advanced Driver Assistance System, or maybe a completely self-governing system. This document employs the chromatic and geometric characteristics of the sign to discern its identity. An issue may arise if the hue of the sign is influenced by a reflection.or if another board resembles a traffic sign. In a similar vein, if a sign is destroyed or severed, its shape is altered and it is impossible to notice. Our algorithm is constantly looking for signals, so even when none are present in the region, it detects signs, resulting in a steady flow of output. This leads to false or superfluous detection. Raising the threshold value for sign detection may help with this. Additional datasets from different countries can be used to tailor and improve overall performance.

License plate recognition: We can use Automatic Number Plate Recognition (ANPR) to recognize license plates. This technology uses optical character recognition on photographs to read vehicle

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registration plates and obtain vehicle location information. It can use pre-installed closed-circuit television, traffic enforcement cameras, or cameras designed specifically for the purpose. Police departments around the world use ANPR to enforce the law, including assessing whether a vehicle is licensed or registered. It is also used by highway authorities and other pay-per-use road operators for electronic toll collection and traffic flow categorization.

Text intimidation and fine generation occur once the license plate number has been recognized and stored in a data manager. Working with the local traffic authority allows you to simply obtain license plate information. We can host a SQL-based online application that can calculate a fine based on defaults and then generate a text message that can be sent directly to the defaulter once we have their information. El.

IV RESULTS

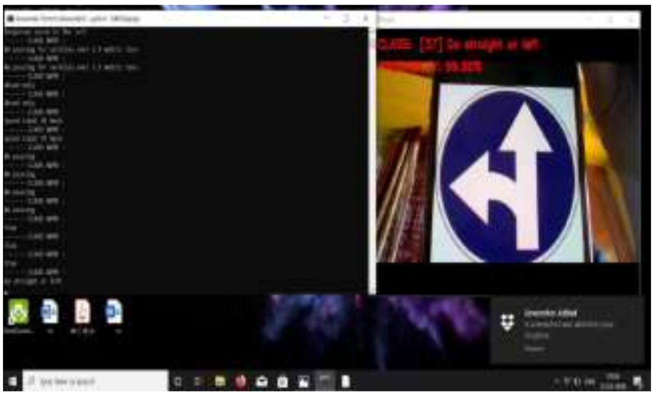

Fig: Detected Traffic Sign (GO STRAIGHT OR LEFT)

Fig:Detected Traffic Sign (AHEAD ONLY)

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Fig: Detected Traffic Sign (DANGEROUS CURVE TO THE LEFT)

Fig:Detected Traffic Sign (SPEED LIMIT 30KM/HR)

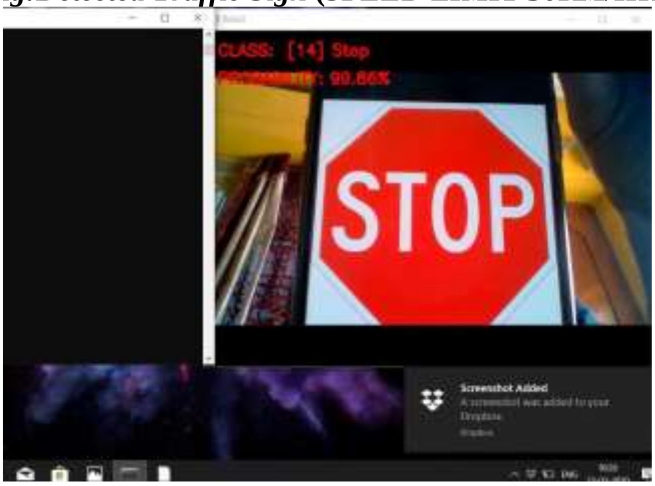

Fig:Detected Traffic Sign (STOP)

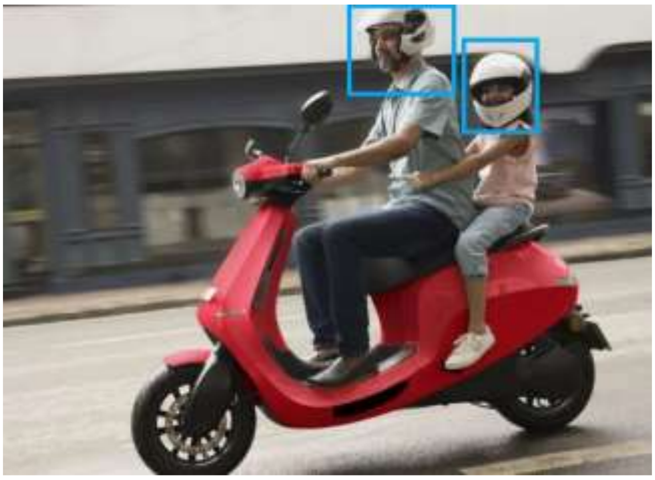

Fig:Helmet Detected

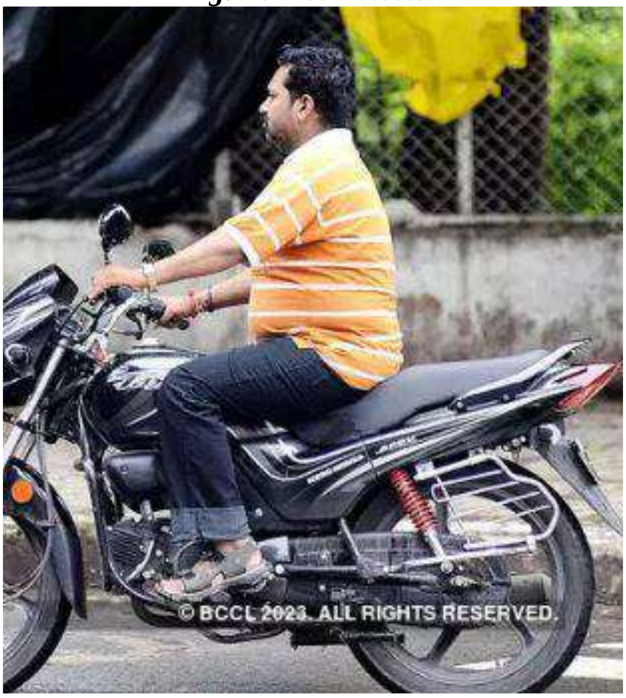

Fig:No Helemet Detected

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