

HELMET RULE VIOLATION DETECTION USING DEEP LEARNING

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Abstract- The widespread non-compliance of helmet-wearing regulations among motorcyclists in India poses a significant threat to road safety. This paper introduces a new approach to address this issue through the developing a Helmet Rule Violation Detection system. Given the challenges faced by traffic police in enforcing helmet regulations, the proposed system leverages computer vision techniques to automatically identify motorcyclists without helmets. The methodology involves the detection of moving vehicles through thresholding, followed by a classification process based on area and aspect ratio to distinguish between motorcyclists and non-motorcyclists. The subsequent identification of helmet violation is achieved by isolating relevant blobs and employing a classification mechanism. By automating this process, the system aims to reduce the burden on traffic police and enhance the overall safety of road users. The proposed approach not only contributes to the mitigation of helmet rule violations but also promotes responsible road behavior, fostering a

safer and more compliant traffic environment in India.

1. INTRODUCTION:

Presently a day's parcel of mishaps will be happened by the carelessness. For this handle activity administration passed a few strict rules like wear head protector, put situate belt and take after the enlightening. For this handle here take one video and apply to the blob discovery and after that for the classification apply to the neural network algorithm. Utilizing this handle we will maintain a strategic distance from the mishaps. And improving the activity administration frameworks.

In spite of being the moment most crowded nation within the world, India has the world's tenth greatest economy[1]. In a thickly populated country like India, motorbikes are the foremost conservative and helpful mode of portability. Head protectors are implied to secure the head, which could be a exceedingly defenseless parcel of our body, and they may be fundamental for all cruiser riders. Bike mischances can result in extreme brain wounds, and wearing a head protector can spare your life.

To keep an eye on Surat's cruiser riders, the SMC (Surat Civil Organization) made India's to begin with real-time CCTV framework. To rebuff bike

riders who don't wear protective caps, SMC formulated the e Challan Framework in India[4].

In any case, activity police must physically recognize non-helmet riders within the control center, which may be a time-consuming assignment owing to overwhelming activity and cannot be connected with the same adequacy 24 hours a day, seven days per week.

So, this work presents an picture handling technique for recognizing bikers who are not wearing head protectors. This methodology will moreover advantage Surat activity police, bringing down the ethical quality rate caused by cruiser accidents. Section II gives a look of earlier work on mechanized protective cap recognizable proof. Segment III gives our approach for automated protective cap location. Area IV presents the paper's extreme result and conclusion.

Motion acknowledgment may be a energetic field of ponder that looks for to join gestural communication into human-computer interaction.

There are two fundamental sorts of motion capture systems: device-based and vision-based.

In vision-based frameworks, cameras collect movements. The vision-based strategy contains a noteworthy advantage due to its need of imperatives

1.1 Existing System:

In this existing we are taking algorithm as support vector machine it will take hyper plane to divide data into test and train like input data and database. It will give moderate output using region of interest and moving object but we cant detect exact are of the face to detect the helmet.

1.2 Disadvantage:

Inability to detect moving objects: One of the significant drawbacks of the project is its

incapability to accurately detect and track moving objects. This limitation severely hampers its effectiveness in scenarios where real-time monitoring of dynamic environments is essential, such as surveillance systems, traffic management, or robotics applications. Without the ability to detect moving objects, the project may fail to provide timely and relevant information, leading to potential safety hazards or inefficient operations. Failure with large datasets: When confronted with a large dataset, the system struggles to process and analyze the information effectively. This limitation impedes its scalability and performance, as it may become increasingly slow and prone to errors when handling substantial volumes of data. Consequently, tasks that require processing extensive datasets, such as big data analytics or complex pattern recognition tasks, may be severely compromised. The inability to efficiently handle large datasets not only undermines the system's reliability but also diminishes its practical utility in scenarios where comprehensive data analysis is paramount. Identification limitations to single motor cycles: Another significant disadvantage of the system is its restricted capability to identify only single motorcycles. This limitation severely constrains its applicability in scenarios where the detection and differentiation of multiple motor vehicles are essential, such as traffic monitoring, parking management, or security surveillance. By failing to accurately identify and classify multiple motorcycles simultaneously, the system may provide incomplete or inaccurate information,

compromising its overall effectiveness and reliability in diverse real-world applications.

2. LITERATURE SURVEY

[1] Akanksha Soni, Arun Pratap Tej Singh's "Automatic Motorcyclist Helmet Rule Violation Detecting using Tensorflow & Keras in OpenCV",IEEE,2022.

Motorcycle accidents have been on the rise in many countries over the years, often due to riders globally neglecting road safety, resulting in accidents and fatalities. One solution is using Support Vector Machines to detect vehicles and distinguish between those with and without helmets. TensorFlow, a library developed by Google Brain, has the capability to classify different objects inside a single outline. This system can also detect heads, enabling the classification of motorcyclists with or without helmets. It's versatile, able to handle scenarios like riders wearing helmets, not wearing helmets, passengers with or without helmets, or even with their faces covered. However, it's important to recognize that the system, relying on convolutional neural networks (CNN), may face limitations based on the available training data. Different helmet types or facial coverings could potentially increase the rate of false recognition.

[2] J. Sivaraj, R.S. Sudhan chand Adithya, Adhavan Alexander's, M.Vishnudeep case "Helmet Violation Detecting Application for

Road Safety ", International Research in Journal of Engineering and Technology (IRJET),2021.

The application aimed to decrease accidents caused by not wearing helmets, promoting road safety. It used a YOLO v3 framework that was custom trained for helmet detection on motorcyclist. The system consisted of three parts: Bike Rider Detection, Helmet Detection, and scanning face images of riders without helmets. It used Vector machine classifier to determine the bike riders without helmet. This model used Circle arc detection to identify the objects. This model took 11.58 milliseconds to process a single frame.

A limitation of this method was that it tried to locate bonnet in the entire frame which was processing power intensive and also it could confuse any other similar shaped objects as helmets. Dedicated hardware was required to set this up so it was not as efficient as the other models.

[3] Felix Wilhlm Sieberta, Hanhe Linb's "Detection of motorcycle helmet use with deep learning",IRJMTS,Volume:03,2018.

Video footage randomly collected from Myanmar was first processed into 150-frame blocks each. Introduction to algorithms with pre-learned loads, implementation records used by receivers and implementation algorithms, with the resorflow of the relaxed and pre-trained. Python Keras The example was implemented using a library. The

helmet detection results of the algorithm were tested on test data, using the best models generated in the validation set.

A limitation of this project is that in many cases two people were riding a motorcycle, and the artist could not tell whether the person in the background was wearing a helmet or whether more than one person was wearing a helmet or not, and accuracy for CNN the network is low.

[4] Ajith R, Sharan, Prajwal, L Shreyas, Navya Shree's, " A Survey On Helmet Detecting of motorcycle Number Plate Recognition For Safety And Surveillance System"

This example revealed that motorcycles were frequently used for daily transportation due to their high cost leading to more accidents. Many of these accidents resulted in head injuries, often caused by motorcyclists not wearing helmets. Since many cities had surveillance systems for safety, they could be used to identify non-helmet manufacturers. It required the use of machine learning techniques, especially CNN (Convolutional Neural Network), to obtain clear images despite challenges such as unique lighting and weather conditions. In this example, there were four separate steps.

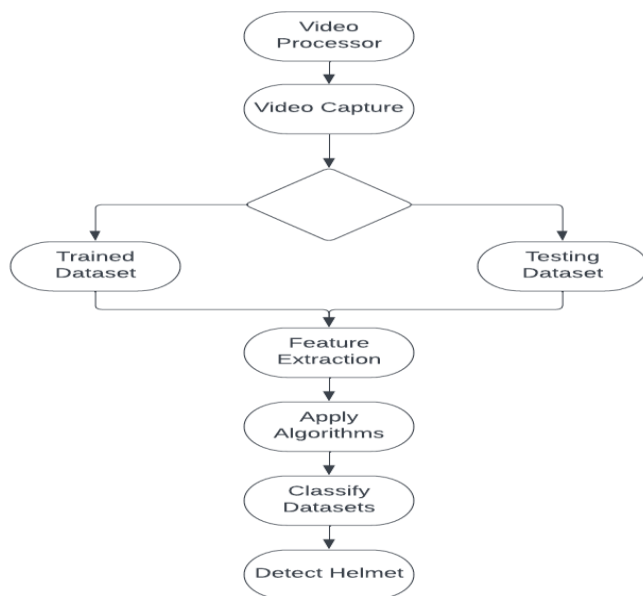
3. Methodology

3.1 Proposed System:

Utilization of Deep Learning Technology for Helmet Detection:

In this following method, deep learning technology is employed for the identification of helmets with reduced processing time while ensuring superior output quality. Deep learning techniques, particularly convolutional neural networks (CNNs), Due to their capability to automatically learn hierarchical features from raw data, deep learning models are well-suited for image recognition tasks. This understanding is derived from training these models on large datasets of annotated images., the system can effectively identify helmets in diverse and complex visual environments.

Feature Extraction for Identification of Human Face, Head, and Helmet: The proposed method involves feature extraction techniques to facilitate the detection of human faces, heads, and helmets within images. Feature extracting algorithms are applied to isolate relevant characteristics or attributes from the input data, such as color, texture, or shape, which are indicative of the presence of faces, heads, and helmets. By extracting discriminative features from the image, the model can accurately localize and differentiate between different things of interest, including human heads and helmets. **Blob Detection for Helmet Tracking:** Blob detection algorithms are utilized for tracking helmets within the image and video stream. Blob detection methods identify regions in the image that exhibit significant variations in intensity or color, typically indicating the presence of distinct objects or entities.



3.2 System Architecture:

3.2.1 Capturing Video: Processes started with captured video footages, typically from surveillance cameras, dash cams, or any other video recording device. Video Frames Extract: The video captured then broke down into single individual frames.

3.2.2 Detecting: Blobs detection is engaging to identify regions within frames that might contain helmet. Blobs typically define as regions of an image that share common properties, such as color or intensity.

3.2.3 Extracting Feature: Features are extracting from detected blobs to represent the distinguish characteristics of potential helmets. These features could include shape, colour, texture, or any others relevant visual cues.

3.2.4 Train: Using extracted features, a dataset is compiling. This dataset consist of labeled image, here each image annotating to indicate whether or not contain a helmet. This dataset then using to

train the neural network.

3.2.5 Neural Network Architectural: A neural network architecturing, typically a convolutional neural network (CNN), chosen or designing for helmet detection task. During training, the network learning to map input images to their corresponding helmet/non-helmet labels by adjustment its internal parameters through optimizing algorithms like gradient descent.

3.2.6 Helmet Detecting: Once neural network trained, it capably of accurately detecting helmet in new, unseen images. The trained model applying to video frames to identify regions containing helmet. This detection process may involving techniques such as sliding window detection or object localization. This could involve generating alert for helmet violations, logging data for analyzation, or triggering automated responses.

3.3 Modules:

3.3.1 Video Streaming: Video livestreaming processing and Computer Vision, video processes is the action of retrieve a video from a source, typically hardware systems like cameras, sensors, and so forth.

3.3.2 Preprocessed: Video preprocessed is the steps undertaken to format videos before being used for model training and inference, enhancing its quality and usability for machine learning models.

3.3.3 Feature Extraction: This implies selecting the most pertinacious attributes or characteristics from raw data, addressing missing values or errors,

standardizing the scaling of features for fair comparisons.

3.3.4 Feature Analyze: Is a vital step in comprehend the relevancy and impact of individual features on a provided dataset, aiding to unearth patterns, relationships within data. By examining the statistical properties and distributions of features, we can obtain insights into their contribution to the overall problem.

3.4 Applications:

3.4.1 Traffic Law Enforcement: This project could support traffic police in enforcing helmet-wearing mandates more effectively and consistently.

3.4.2 Accident Precaution: By detecting and penalizing helmet regulation violators, it assists in reducing head traumata and fatalities in motorcycle incidents.

3.4.3 Automated Law Enforcement: The mechanism can automate the procedure of detecting violations, lessening the workload on traffic police and enabling their to focus on other imperative tasks.

3.4.4 Data Collection: The project could generate valued data on the frequency and locations of helmet regulation infractions, assisting in traffic handling and incident analysis.

3.4.5 Public Awareness: The noticeable implementation of helmet regulations through automated systems can boost public awareness about the significance of helmet usage and protection to traffic regulations.

3.4.6 Safety Enhancement: By discouraging helmet regulation breaches, it improves overall road security for motorbike riders.

3.4.7 Integration with Smart Cities: In smart city initiatives, such technology can be integrated into traffic administration systems for immediate monitoring and enforcement.

3.4.8 Insurance Premium Estimation: Insurance corporations can apply data from such systems to evaluate risk and determine premiums for motorbike riders.

3.4.9 Exploration and Analysis: The amassed data can be used for exploration on traffic safety and rule obeisance, leading to probable enhancements in road constructions and regulations.

3.4.10 Customized Enforcement: Authorities can use the data to focus enforcement efforts on areas with high violation rates, enhancing the efficiency of law enforcement.

3.5 Algorithms used

3.5.1 Blob Recognition: Blob recognition is a computer cognition technique used to identify regions in an image that share mutual properties, such as color or intensity. The term "blob" pertains to a group of interconnected pixels that form a distinct product or region within an image. Blob recognition algorithms are frequently employed in different applications, including object tracking, image segmentation, and feature extrapolation.

Here's a universal overview of how blob recognition operates:

Thresholding: In several instances, blob recognition commences with thresholding, where an image is converted are considered foreground (usually white), while those below are considered background (usually black). **Connected Component Analysis (CCA):** After the image is thresholded, connected component analysis is implemented to identify connected regions of pixels. A connected component is a set of pixels that are connected to each other in some manner, typically through adjacency. **Blob Filtration:** After recognizing connected components, blob recognition algorithms frequently employ filtration grounded on specific criteria to differentiate blobs from noise or other unwanted regions.

Feature Extrapolation: Once blobs are recognized and filtered, various features can be extrapolated from them, such as centroid coordinates, area, perimeter, and shape descriptors (e.g., circularity, elongation).

Post-processing: Depending on the application, additional post-processing steps may be employed to further refine the detected blobs or to perform specific tasks such as tracking blobs across multiple frames in a video sequence.

3.5.2 Profound Neural Systems (DNNs):

Profound Neural Systems, a sort of fake neural organize (ANN), are recognized by having numerous layers between the input and yield layers, empowering them to memorize progressive representations of information. DNNs have picked up critical ubiquity and appeared surprising victory over different spaces, counting computer vision,

common dialect understanding, discourse acknowledgment, and fortification learning.

Neurons (Nodes):

Neurons are the basic computational units inside a neural network. Each neuron gets input signals, forms them employing a set of weights and predispositions, and creates an yield flag. In DNNs, neurons are organized into layers.

Layers:

A ordinary DNN comprises of an input layer, one or more covered up layers, and an yield layer. Each layer contains numerous neurons, with neurons in adjoining layers associated to each other through weighted associations.

Actuation Capacities:

Activation functions present non-linearities into the arrange, permitting it to capture complex connections within the information. Common enactment capacities incorporate sigmoid, tanh, ReLU (Corrected Direct Unit), and softmax.

Feedforward Proliferation:

Amid feedforward engendering, information streams through the arrange from the input layer to the yield layer without any criticism circles. Each layer computes a weighted entirety of the inputs, taken after by the application of an actuation work to create its output.

Backpropagation:Backpropagation could be a significant calculation connected to penetrate DNNs. It envelops computing the angle of the

misfortune work with regard to the organize parameters (weights and inclinations) and leveraging this slope to update the parameters in a way that minimizes the misfortune work. This handle is commonly performed utilizing optimization calculations such as stochastic slope plummet (SGD) or its variations.

Significant Learning Models:

DNNs can be organized into assorted models grounded on the associations between layers. A few routine designs comprehend:

Altogether Associated Systems (FCNs):

Moreover recognized as thick systems, where each neuron in a layer is associated to each neuron within the adjoining layer. Convolutional Neural Systems (CNNs):

Particularly successful for handling grid-like data such as pictures, CNNs utilize convolutional layers to extricate spatial progressions of highlights.

Repetitive Neural Systems (RNNs):

Suited for consecutive information like content or time arrangements, RNNs have associations that shape coordinated cycles, permitting them to hold data over time. Amplified Short-Term Memory Systems (LSTMs) and Gated Repetitive Units (GRUs):

Variations of RNNs planned to address the decreasing angle issue and way better capture long-range conditions in consecutive information.

Transference Learning:

Transference learning is a method where a pre-trained DNN demonstrate is fine-tuned on a modern mission or dataset. This approach misuses the information learned by the pre-trained

demonstrate and as often as possible leads to speedy merging and made strides execution, especially when labeled information is restricted.

Regularization:

To upset overfitting, which emerges when a show learns to memorize the training information rather than generalize, different regularization methods can be connected to DNNs. These include dropout, physical property rot (L2 regularization), and early capture.

5. Experimental Results

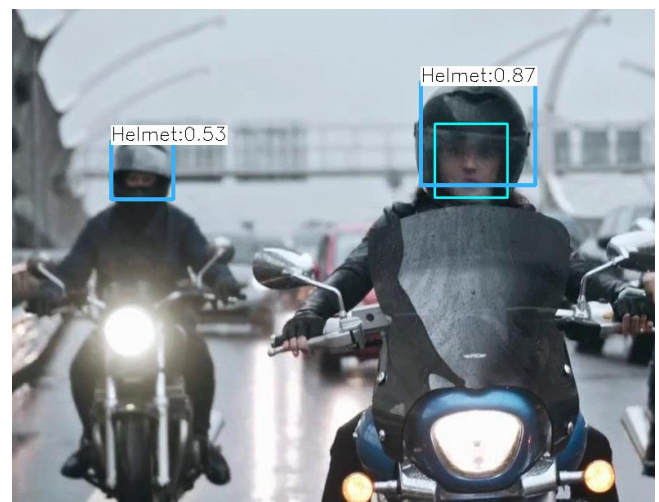


Fig 5.1: Depicting helmet detection

As we can see above, helmet is detected with an accuracy of 87 percent.

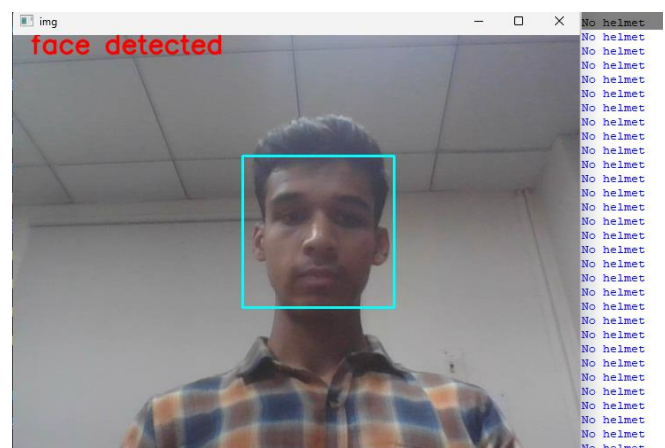


Fig 5.2: Depicting no helmet detection

As we can see in the above picture, the face is detected without helmet

motorcycle Number Plate Recognition For Safety And Surveillance System”

6. Conclusion:

Secure helmet wearing detection is a mighty task for look-after surveillance in power substation. In this we can avoid accidents using algorithm. For future purposes we can use hardware parts.

Suggesting potential areas for future enhancements or research. This could include improving the detection of specific helmet types, extending the system to detect other safety gear, or exploring alternative object detection algorithms.

7. REFERENCES

[1] Akanksha Soni, Arun Pratap Singh “Automatic Motorcyclist Helmet Rule Violating and Detection using Tensorflow & Keras in OpenCV”,IEEE,2020.

[2] J. Sivaraj, R.S. Sudhan chand Adithya, Adhavan Alexander, M.Vishnudeep “Helmet Violation Detecting Application for Road Safety “, International Research in Journal of Engineering and Technology (IRJET),2020.

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[4] Ajith R, Sharan, Prajwal, L Shreyas, Navya Shree,: “ A Survey On Helmet Detection of