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Automated Detection Approach based on Video Processing to identify the Bike-riders without Helmet in Real Time

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Abstract:
A novel approach is propose to perform the recognition of helmet utilization destructions among the bikers. The methodology involves the integration of the object detection algorithm with Deep Learning based Generative Adversarial Networks (DL-GANs). This helps to improve the accuracy of current helmet destruction recognition methods, which are frequently based on manual inspection and prone to errors. The suggested approach uses a large dataset of real and artificial photos to train the model, and it shows improved accuracy in detecting helmet violations, even in situations where there are several riders. Data augmentation is used to increase the volume of training data, especially for imbalanced classes, in conjunction with artificial images generated by CNN-GANs. This improves typical generality towards practical circumstances. The impartial DL model determines F1 score of 0.91 throughout everyone by 0.617 assurance level, however, the DL based model totaled 0.96 at 0.334 confidence level. These data suggest that proposed DL-GAN can improve helmet rule detection accuracy, leading to safer motorcycle practices.

Keywords: Neural Networks, Helmet Violation, Deep Learning, Artificial Intelligence, Image Detection.

I. INTRODUCTION

Motorcycles are popular for their versatility and cost-effectiveness as a form of mobility. Motorcycles occupy smaller places, reducing circulation bottleneck and providing rewards in partial space places. As a result, motorbikes are extra desirable in situations with mixed and unorganized traffic in crowded cities because riders can move more freely to avoid obstacles [1].

Motorcycles are much more fuel-efficient than passenger cars, which contribute to their extensive use in developing nations, especially for delivery and business purposes [2]. Motorcycle riders have a higher risk of fatal crashes, which may be due to many variables [3, 4]. First of all, riders have a tendency to be less risk-aware, which makes them more likely to break the law and participate in hazardous activities (such spot filtering and abrupt overtaking) more frequently [5] and [6]. Second, riding a motorcycle may be linked to untrained and inexperienced driving [7]. Lastly, because they don't have as much protection, motorcycle riders are more prone to injuries [2] and [8]. To advance motorbike well-being, it's important towards discourse the aspects that contribute to high deaths and enforce stronger traffic regulations to discourage dangerous riding practices. Many countries have laws that require people to wear safety goggles because they have been shown to decrease the severity of injuries in motorcycle accidents [9]. Helmet laws have been convincingly shown to be an essential first phase in raising motorbike protection and lowering the amount of crash-related deaths [10]. As this happens, there is increasing attention, now the application of automated algorithms for helmet recognition that might remain utilized in less structured driving situations. The variability in the dataset once around several qualifications and trashy filmed recordings offers challenges for these systems.Detection methods typically rely on advanced machine learning algorithms and vast datasets. In high-traffic areas with little enforcement, the number of motorcycle riders wearing helmets may be low. Since more motorcyclists are wearing helmets than are not, the dataset becomes skewed in favor of the former. A multitude of frameworks have been put out to handle these datasets [11].

Generative adversarial networks (GANs), for example, can improve training dataset quality by correcting for class imbalance [12] and [13]. The discriminator's job is to ascertain how well the feedbacks match the innovative delivery or the circulation that the creator selected. The generator is in charge of making fake observations. These neural networks are trained until the discriminator fails to accurately identify true or bogus observations due to the generator's well-sampled data. GANs can make extra statistics and enhance the amount of explanations happening unstable datasets. Our tests' results indicate that the framework chosen can accurately identify motorcycle riders who wear helmets, indicating the possibility of using this system for automated enforcement [14 – 16].

This education aims towards create a context aimed at detecting motorbike riders' helmets, addressing class imbalance difficulties from earlier research. Then, by using this structure, helmet use laws may be enforced, hence increasing overall traffic safety.

The work primary contributions are stated as follows:

- Created an instantaneous helmet destruction recognition system using DL, documents growth, and DL-GANs for accurate detections in different weather and light circumstances. In attempt to overcome the occlusion and perspective issues, this work employed data augmentation and generation approaches, as well as assessment period increase during the inference step to further boost prediction accuracy and confidence.
- To Determine the three entity recognition replicas of Feature Extraction series such as, HOG, SIFT, and LBP as it performs best for detecting helmet violations by analyzing the created system's performance. This study contributes to improve the accuracy of helmet violation detection.

II. VARIOUS EXISITNG WORK RELATED TO HELMET USAGE AND DETECTION METHODS

Although mandating the use of helmets is crucial for lessening the severity of motorbike accidents, this procedure could be seen as expensive. This is particularly valid for areas with little resources for law enforcement. To address these difficulties, computerized helmet recognition structures is identified. Item recognition is the process of identifying and locating items, such as motorcyclists without helmets, in movies or photos by image processing or deep neural networks. There are some of the processes involved in image processing for object detection. [17-19] are some of the different ways that people have suggested to find things in pictures. In addition, deep learning techniques have become the industry standard because of their flexibility then capacity towards switch practical situations [20]. These methods can recognize intricate patterns. Convolutional neural networks (CNNs) are used in feature extraction approaches, including Region-based CNN (R-CNN) [26], Fast and Faster R-CNN, Single Shot Multi-Box Detector (SSD), and You Only Look Once (YOLO) [28-30]. YOLO is a common approach for detecting objects in current time due to its speed and efficiency. The aforementioned method has been employed in multiple research investigations to identify diverse objects, including helmets [21], license plate and road users engaged in conflict [22]. Recently, many kinds of changes have been made to the model architecture, which has increased accuracy and decreased processing time [23]. The fact that these models are readily implemented, come with pre-trained weights, and are open-source make them highly valuable for picture detection. They are also constantly being improved. However, the excellence of the drill dataset might have a partial impact on the accuracy of Yolo models.

More methods based on deep learning can be used to fix this issue. Helmet detection techniques are the subject of several investigations. For instance, [24] employed a DL indicator towards double stages towards identify helmets in China. The detector initially identifies a scrambler and subsequently monitors helmet usage. Furthermore, [25] suggested an architecture that uses deep learning to confirm Myanmar's helmet usage among motorcycle riders. The program has an accuracy of about 5% lower than a human observer. A comparable strategy was employed by [26] and [27] for motorcycle riders in Thailand, and the technique revealed a minimal number of false positives. Furthermore, [28] employed

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support vector machines to detect helmet wear in crowded settings. Existing research on helmet identification algorithms often uses conventional backgrounds otherwise classifiers with real data [29]. These techniques lose some of their effectiveness, though, in extremely crowded areas where there are several infractions taking place in one scene and there is little visibility.

Generative adversarial neural networks have been popular for their capacity to create realistic false images. Dissemination systems incorporate arbitrary sound into the replicas towards facilitate the sample construction development, and vibrational auto encoders, which employ Algorithms 2024, 17, 2024 of 16 making them part to guarantee the generation of sufficient data, are two other methodologies. In order to address the drawbacks of low visibility and unequal class distribution, this research suggests a paradigm that takes synthetic data into account. Generative adversarial networks can improve model accuracy by optimizing the training process. This study explores various models to enhance helmet recognition and categorize motorbike conditions that violate traffic restrictions.

III. SEGMENTATION AND DETECTION METHODS

Image Segmentation performs both interactive and automatic jobs for segmentation in a single model. Before, dynamic segmentation could separate any type of object, but someone had to

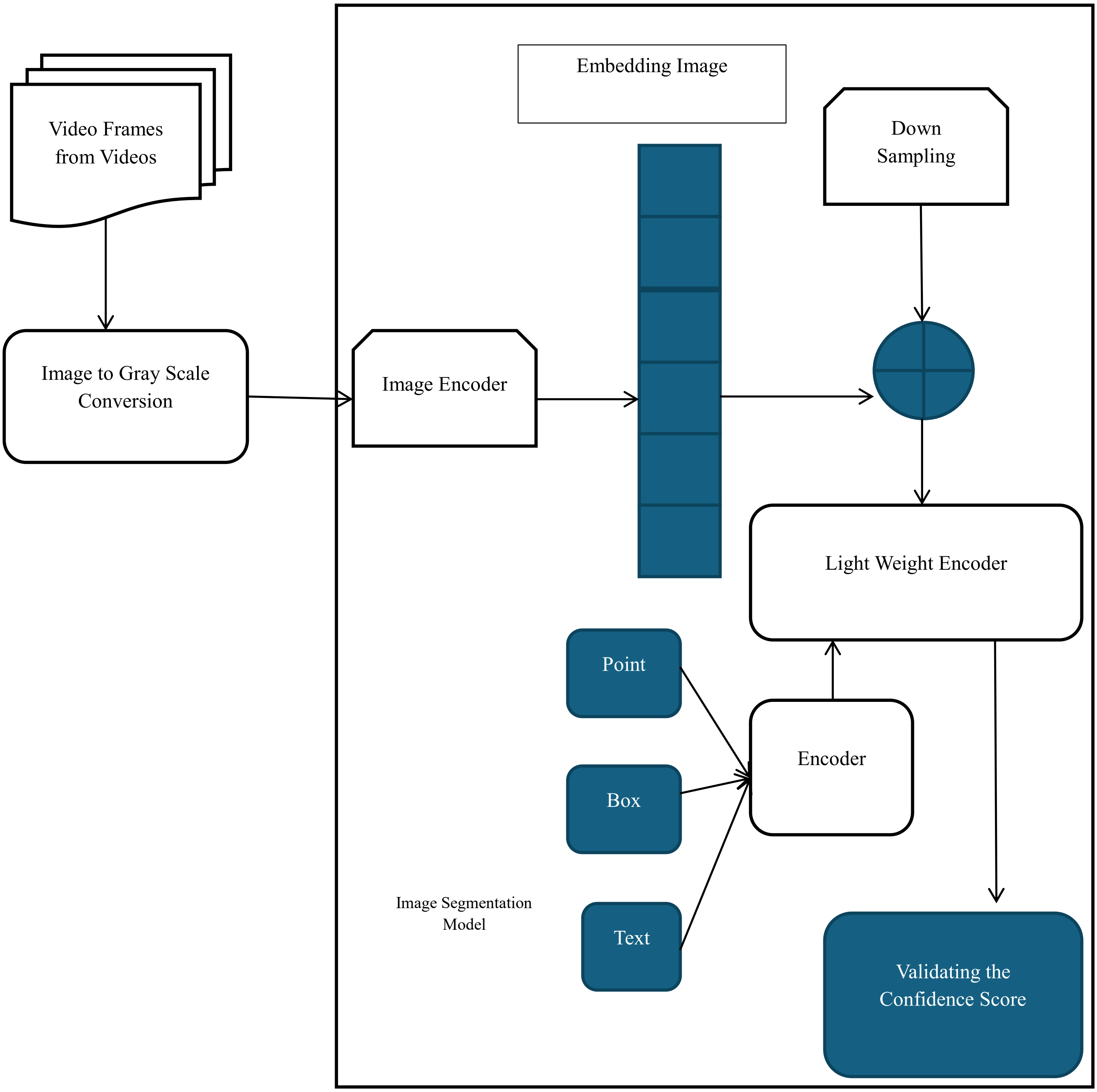

Figure 1. Image Segmentation Architecture

control the process by improving a mask repeatedly. Automatic segmentation in Image Segmentation lets you divide objects into groups that you choose ahead of time. It's very flexible because its layout can be changed. So, Image Segmentation can handle many different segmentation jobs with the right prompt, like boxes, clicks, text, and more. A diverse and insightful dataset of over 1 billion masks is used to train Image Segmentation, which enables it to identify novel objects and images that are not present in the training set. These new frameworks will greatly change CV models used in many areas, including self-driving cars, security, and virtual reality. Objects around self-driving cars, like other

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cars, people, and traffic signs, can be found and separated by Image Segmentation. In augmented reality, Image Segmentation can divide the real world into sections so that virtual items can be placed where they belong. This makes the user experience more realistic and interesting.

Image Segmentation Algorithm:

Input: Gray Scale Image

Output: Image Validation

```
Initialize the Image
{
        Encode the image
Embedding the Image into several Groups
Integration of various groups and down sampling
        Down Sampling is performed with image masking
To obtain light weight mask decoder
        Added with encoder with image prompting
        Image prompting added with
        {
                Points
                Box
                Text
        }
}
Validate the image masking
        Calculate the Confidence Score Value
```

The suggested two-phase real-time helmet-free bike rider identification method is presented in this section. During the initial stage, we identify the presence of a cyclist in the audiovisual setting. Trendy the subsequent stage, the cyclist's bean is identified and determine if a helmet is being worn or not. To mitigate inaccurate forecasts, we amalgamate the outcomes from successive frames to obtain the ultimate projection. The process structure is depicted in Figure 1 illustrates the sequential stages of the standardized background, including contextual deduction, attributes mining, and item organization by model structures.

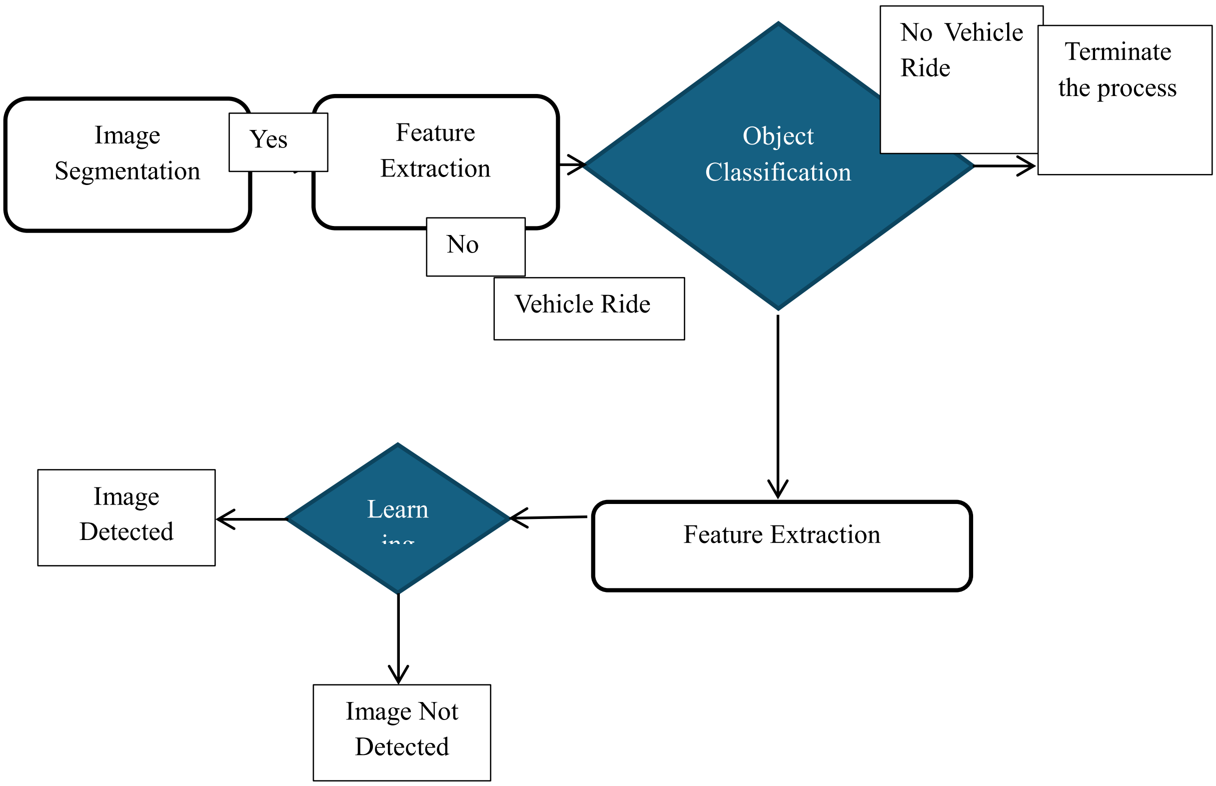

Figure 2. Image Detection Model

Since a helmet remains individually important when a bike rider is moving, processing the entire frame adds computational cost and has no effect on the detection rate. To continue, we utilize background subtraction on grayscale frames to differentiate between items that are in motion and objects that are stationary. Here, we outline the sequential procedures of backdrop modeling. Background modeling is denoted as the development of generating an image representation for a given background scene. The background subtraction approach in [9] is first applied to distinguish moving items, such as, bikes, people, and cars, from stationary objects, like trees, roads, and buildings. Nevertheless, there are certain difficulties encountered when working with data obtained from a solitary camera. Environment factors act as a challenge towards improve and modernize the backdrop after a constant tributary of structures include shadows, swaying tree branches, variations in illumination during the day, and other abrupt changes. When faced with intricate and fluctuating scenarios, a single Gaussian model is inadequate to fully capture these variations [10]. For each pixel, it is essential to utilize a varied amount of Gaussian models because of this rationale.

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Adaptable quantity of Gaussian mechanisms facilitates the circumstantial replica's ability to effortlessly modify its parameters based on the circumstances. Nevertheless, certain errors may persist as a result of the existence of highly obscured objects and blended shadows. Let's consider the variables I1, I2, and so on...The value represents the brightness level of a pixel for the previous t consecutive frames. At time t, the probability of witnessing an intensity value of an image pixel is determined based on image classes in the background have Gaussian components with low variation and high weight, while classes in the front have components with high volatility and low weight.

Subsequently, the processed frame is divided into segments according to the boundaries of the objects. The background subtraction approach retrieves only moving items and ignores static objects. However, the numerous objects that are not of interest to us as the objects includes vehicles and humans. These things are sorted or selected based on their region. The purpose of this is to exclusively focus on things that are highly probable to belong to the category of bike riders. It aids in diminishing the intricacy of subsequent procedures

Phase I: Identification of Vehicle Riders

This stage entails the identification of individuals riding vehicles within a certain frame. This stage utilizes objects in Bjs, which are the prospective bike riders obtained from the backdrop demonstrating step. These objects are classified as either 'bike-rider' or 'others' established and scheduled their graphical characteristics. This stage has double phases: Attribute mining and image categorization method.

- **Attribute Mining:** Item arrangement necessitates the utilization of appropriate visual feature representations. HOG, SIFT, and LBP have been demonstrated as effective techniques for item recognition in literature. To understand how to achieve this objective, we examine the following characteristics:
- **Histogram of Oriented Gradients (HOG)** descriptors have demonstrated exceptional efficacy happening item recognition [12]. These descriptors represent confined outlines via analyzing gradients.
- **Scale Invariant Feature Transform:** This method looks for important locations inside the picture. For every key point, it retrieves feature vectors [13]. The descriptors exhibit robustness in various situations due to their ability to maintain scale, rotation, and illumination invariance. We employed the sack of confrontations methodology towards construct a language L consisting of several terms. Planning SIFT descriptors to V outcomes in a attribute routes, where s belongs to the set of real numbers Rn, and the dimension n is equal to 5000 Pixel. The attribute routes s is utilized towards ascertain the resemblance of photographs.
- **Local Binary Patterns (LBP)** are a set of characteristics that are used to collect texture information within an image frame [14].

The phase-I categorization patterns are shown in 2-D space using t-SNE in Fig. 2 [15]. The two classes such as, "bike-riders with helmet" and "Biker-riders without helmet" fall into nearly different regions. This demonstrates that the feature vectors effectively capture the action and contain distinguishing information, which in turn raises expectations for high classification accuracy.

Categorization: Following the process of feature extraction, the subsequent step involves categorizing the extracted features as either 'bike-riders' or 'other' objects. Therefore, this necessitates the use of a binary classifier. Any binary classifier can be utilized in this context. However, we have opted for ML resilience happening achieving accurate arrangement results, level once skilled with a limited amount of feature vectors. In addition, we employ various kernels, including radial basis function (RBF), linear, and sigmoid (MLP), to determine the optimal hyper-plane.

Phase-II: Identification of Motorcyclists deprived of Helmet

Once the motorbike riders have been identified, the subsequent stage involves ascertaining whether or not they are wearing a helmet.

Conventional look recognition methods not enough for this stage outstanding to the resulting factors:

i) It is quite difficult to catch face characteristics like the lips, nose, and eyes at low resolution.
ii) The bike may be moving at an oblique angle.

In such instances, the face may be completely obscured. The suggested framework first identifies the area surrounding the head and then proceeds to ascertain whether the bike-rider is wearing a helmet or not. The proposed framework utilizes the fact that the helmet is likely to be positioned in the higher regions of the bike rider's head to attempt to locate the head of the bike rider. The efficiency of this process is seen in our phase-II classification results. The proposed method also takes less time to compute than the Circle Hough Transform (CHT) is a simple feature extraction approach used in digital image processing to find circles in defective images. The process of "voting" in the Hough parameter space and choosing local maxima in an accumulator matrix yields the circle candidates. [17].

- **Attribute Mining:** The bicycle rider's helmet usage is determined by analyzing the region surrounding their cranium. Similar features from phase I, such as HOG, SIFT, and LBP, are employed to do this. Figure 3 illustrates the patterns for phase-II in a two-dimensional format using t-SNE, as described in reference [15]. The two classes, "non-helmet" and "helmet", drop towards overlying sections according to the distribution of the HOG feature vectors, demonstrating the complexity of representation.

- **Classification:** The technique must ascertain whether the rider is breaking the law by failing to wear a helmet, for example. In order to achieve this objective, we will examine two categories:

1. Bike riders who do not use helmets (+ve values),
2. Bikers who use helmets (-ve values, which is indicated below the threshold as bikers uses helmet).

The Support Vector Machine (SVM) is employed for classification by utilizing extracted features obtained from the previous stage. As a way to evaluate the classification outcomes and determine the optimal solution, several combinations of features and kernels are employed. The Result section contains both the results and the analysis.

Consolidation of Results refers to the process of combining and integrating the outcomes or findings obtained from several sources or experiments. Our local results, such as whether or not a bike rider is wearing a helmet, are derived from previous phases. However, up to this point, the relationship between consecutive frames has been disregarded. To be able to minimize the occurrence of false alarms, we aggregate the local findings.

The final global determination on whether a biker is wearing a helmet is made by combining separate local results from frames.

IV. PERFORMANCE ANALYSIS

A. DATASETS:

The study's dataset, which was gathered as part of the 2023 AICity (https://www.aicitychallenge.org/) (accessed on March 20, 2023), consists of 100 Indian videos, each lasting 20 seconds at a frame rate of 10 frames per second and with a resolution of 1920 x 1080. The dataset for each class contained bounding box labels. The dataset presents several challenges due to the various visual complexities caused by weather conditions, glare, and the time of day, as depicted in Figure 1. In addition, the objects in the photos provide additional difficulties such as pixilation and occlusion, which are commonly encountered problems when evaluating images from CCTV cameras. The dataset contains eight classes of interest, and Table 1 lists each class's corresponding frequency.

A significant obstacle related to this dataset is that most scenarios are plagued by varying degrees of mislabeling, ranging from mild to extreme. The mislabeling primarily included omission, as a significant proportion of objects in a frame was disregarded. Often, timestamps were mislabeled as motorcycles and other incorrect labels, potentially compromising the accuracy of any model. This aims to design an approach that takes into account the possibility of inaccurate ground truth and establishes a corrective action. Furthermore, apart from the difficulties related to the absence of precise labeling, the original dataset included of low-resolution photos, which were further complicated by factors like fog and inadequate illumination. Finally, the dataset has imbalanced classes, which necessitates the application of cutting-edge minority oversampling techniques in order to precisely identify these underrepresented classes.

Table 1. Existing models for detecting and analyzing the bike riders.

S.No.	Ref.	Proposed Methodology	Parameters analyzed	Limitations and Future gap
1.	[30]	A machine learning-based method: Determine whether motorcycle riders wear helmets captured still images from security cameras, the item a detection-based algorithm that has been trained to identify motorbikes and their headgear	Using HOG Descriptors, Data collection is attained and 87.6% Accuracy is determined.	Limited to less usage of datasets attained
2	[31]	A fine-tuned YOLOv8 model:Detecting helmetless bike riders and retrieving their license plates. We used numerous augmentation approaches to improve the accuracy and resilience of our model.	mAP is a performance statistic; larger values generally indicate better overall object detection accuracy. 95.2% mAP50	Limitation in the number of Datasets used. Improving motorcycle rider, passenger, and other road user safety
3	[32]	A region-based convolutional neural network (R-CNN) deep learning model Detects helmet violations in videos and applies the appropriate sanctions to drivers who break traffic laws	97.67% accuracy 97.70% precision 97.98% F1 score 98.25% sensitivity.	Adding more features, like number plate detection and other traffic violations
4.	[33]	Automatic helmet detection of motorcyclists' method using an improved YOLOv5 1. Motorcycle detection and helmet detection, 2. Effectively improve the precision and recall of helmet detection.	Average precision (AP) of motorcycle is 98.4% F1 score is 94.0%, - high detection accuracy.	Add a tracking algorithm and detect the same object only once to avoid recurrent detection.
5.	[34]	Automated technology that efficiently identifies motorcycle riders who are not wearing helmets. Adopts faster R-CNN for the recognition of motorcycles in tagged foreground items to ensure the motorcyclists with and without helmets.	Performance metric such as precision (p), recall(r), and average precision (AP) are calculated	Speed estimation of vehicles of the motorcyclists
6.	[35]	Proposed deep learning-based automatic detection approach for worker safety helmets offers an effective possibility to improve safety management on construction sites.	Precision is 95% and the recall is 77%	Need more comprehensive preprocessing operations
7.	[36]	The PRB-FPN+ object detector can identify small things, including helmets, in difficult-to-reach settings like misty scenes or targets with dense clutter or occlusions.	mAP → 05 mAP → 5.95	Multiple object tracking is required
8.	[37]	Detector and identifier for finding the helmet violation Data processing for improve the accuracy of framework	Average Precision (mAP) → Mean of AP values across all object classes.	Tracker to the main framework for ensembled information from several frames to better classify each rider.
9.	[38]	Fundamental subsystem Identifying the bicycle riding environment Open-source trained model MM Segmentation	The ROI extension identification algorithm →highest RTP 0.9 or higher for roadways and 0.95 or higher for sidewalks	Shape and optimization of the ROI Auto-labelling techniques will streamline the process
10.	[39]	The automatic system is designed to detect two-wheeler traffic offences when there are three riders. The two-wheeler and person are detected using the YOLO v8 model. Effectively detects many and closer items in a single image, as well as overlapped objects	Higher precision and recall values	Detecting overspeed

V. PERFORMANCE ANALYSIS

Experimental outcomes were evaluated based on precision, and recall on the validation dataset, and it is a typical metric for evaluating object identification models' performance. Assuming a 50% overlap between the predicted and authentic limit boxes, it calculates the average model precision across all confidence levels. Put simply, it quantifies the model's ability to accurately identify the location of items in a picture, considering both its precision and recall.

$$Precision = TP / (TP + FP) \quad \text{-------------} (1)$$

$$Recall = TP / (TP + FN) \quad \text{-------------} (2)$$

$$F1\,Score = TP / [TP + [(1//2) / (FP + FN) \quad \text{-------------} (3)$$

Precision assesses the percentage of true positive predictions (i.e., the number of encouraging occurrences that are correctly identified) among each favorable forecast generated by the model. A high precision score signifies that the model is producing precise positive predictions and has a minimal percentage of false positives using equation (1). Recall quantifies the ratio of accurately predicted positive cases to the total number of positive instances in the data using equation (2). The F1 score was computed using equation (3), which considers both the precision and recall of the method to yield a unified evaluation of its efficacy.

Table. 1. CLASSIFICATION (%) OF DETECTION OF BIKE-RIDER

Feature Extraction	Linear	Multi-layer Perception	Radial Basis Function
HOG	98.97	82.99	82.99
SIFT	82.99	82.99	82.99
LBF	82.99	82.99	82.99

Table 2. ARRANGEMENT (%) OF 'BIKE-RIDER WITH HELMET' VS 'BIKE-RIDER WITHOUT HELMET'

Feature Extraction	Linear	Multi-layer Perception	Radial Basis Function
HOG	95.77	62.97	62.97
SIFT	64.65	64.65	64.65
LBF	64.65	64.65	64.65

One is perfect accuracy and recall, and zero means the model did not correctly identify any items. The F1 score is between 0 and 1 as represented in Table 1 & 2.

VI. CONCLUSION

This study proposes a background aimed at simultaneous identification of circulation law damage who ride bikes deprived of a helmet. This planned background resolve and help travel cops find people who break the rules when they are in strange places, like when it's hot outside, for example. According to experimental results, the accuracy for detecting bike riders is 98.88%, while the accuracy for detecting violators is 93.80%. With an average processing time of 11.58 ms, this data is appropriate for real-time applications. Additionally, the suggested architecture can automatically adapt to new conditions with minor adjustments. It is possible to expand this framework to identify and report violators' licence plates.

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