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Detection of Two Wheeler Defaulters UsingArtificial Intelligence

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Abstract— *India is one of the developing countries. As the number of personal vehicles increase it also contributes in the development of the nation side by side. It has also increased congestion in urban areas. In a nation with such a large population as India, traffic laws are frequently broken. Accidents linked to these infractions result in significant loss of life and property. Bicycle accidents are more frequent than those involving other vehicles due to the increased usage of bicycles. Not wearing a motorbike helmet is one of the leadingcauses of these. For governments and road managers everywhere, the security of powered two-wheelers (PTWs) is crucial. According to recent government statistics, PTWs account for only 2% of all traffic yet 30% of all fatalities. But given that the estimated numbers are derived by merely counting the number plates that have been registered; they donot accurately represent the number of PTWs on the road at any particular time. Thus, we need a better traffic management framework. The purpose of making a better traffic management framework which is versatile to the current traffic situation. So as to guarantee the well being steps, the identification of violators of the traffic rule is an exceptionally important however testing task because of different troubles, for example, impediment, light, low quality of the surveillance video, changing weather conditions, and so forth. This paper shows a structure for automatic detection oftwo wheeler drivers without helmets in surveillance recordings. Further, a model has been proposed as the result of that study. Emphasis has been put on different techniques practiced with their drawbacks and comparative analysis, eventually suggesting the best practiced implementation.*
Keywords*—CNN, Yolo, Tensorflow*

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I. INTRODUCTION

In India, road accidents account to almost 30% of totaldeaths,40% of major road injuries and deaths are caused you too motorized 2-Wheeler not wearing helmets. In countries, such as India, particularly because of enormous population and low/middle income background status, a substantial number of two-wheeler accidents occur leading to head and traumatic brain injuries.

The rider of a two-wheeler gets flung from the vehicle in the event of an accident because of a quick deceleration. When a head collides with an object, the motion of the head stops, but the motion of the brain is maintained by the mass of the brain until the object strikes the inner section of the skull. This kind of brain injury may occasionally prove fatal. Helmets save lives in these situations. Helmets decrease the likelihood that the skull will slowdown, which reduces head motion to nearly nothing. As time passes, the head comes to a stop after the helmet's cushion has absorbed the impact of the accident. Additionally, it disperses the force of the hit across a wider region, protecting the skull from serious wounds. More significantly, it serves as a mechanical shield between the rider's head and whatever it is they come into touch with. Due to the importance of wearing a helmet, governments have made it illegal to travel on a bike without one and have implemented manual enforcement methods to apprehend offenders.

The current video surveillance-based techniques, however, are passive and heavily reliant on human labour. Due to the participation of humans, whose efficiency declines over time, such systems are typically impractical. Automation of this procedure will greatly minimize the requirement for human resources while ensuring reliable and effective monitoring of these breaches.

According to a report released by World Health Organization (WHO) inappropriate or lack of use of helmets are major/increasing cause of road fatalities involving two-wheelers. In the same report it was mentioned that wearing a helmet can reduce a chance of death by 40% and that of serious injuries by 70%. Although a huge number of contributions have been madein this domain, laws have been imposed and new norms have been introduced to keep the fatality rates to the bare minimum but mostly ineffective. In the last year, automatic systems have become more significant in traffic management. One objective is to increase the effectiveness of a traffic flow system. Other objectives include lowering the cost of labour and reducing accident causes.

One of the main contributing factors to accidents in India is the motorbike rider who does not wear a helmet. Every motorcyclistis required by law to wear a helmet when operating a motorcycle. However, many bikers disregard safety precautions and use their motorbike without them. The policeman made an effort to manually control the issue, but it was ineffective given the circumstances. The optimum approach is to create a programmed system that can automatically identify this type of issue without the need for human intervention. Changing times call for changing and more technology-oriented approach. In this paper a thorough study has been carried out to distinguish between various image detection techniques and models. Further, a model has been proposed as the result of that study. Emphasis has been put on different techniques practiced with their drawbacks and comparative analysis, eventually suggesting the best practicedimplementation.

Although wearing a helmet is required by the regulation, most people opt not to. One of the helmet's key goals is to ensure the riders' safety. This idea intends to provide an automated method for law enforcement to ascertain if a rider is equipped with a helmet or not and to fine defaulters. Two-wheelers are growing in popularity in modern times due to their low cost and ease of handling. Roadside accidents have, regrettably, become more frequent as a result of this. A helmet is amongst the most crucial elements in guaranteeing the safety of bike riders. Many people decide not to wear a helmet despite being well aware of this problem.

According to a 2018 survey, nearly 57% of Indian motorcycle riders choose not to wear helmets in defiance of the law. To make sure this does not happen, the government has begun implementing numerous systems that use live CCTV investigation to detain riders who are not wearing helmets and penalize them in addition to issuing an e-Challan. However, this arrangement still requires human involvement to manually detect riders without helmets from the control room's video surveillance system, which lowers the model's effectiveness because it is susceptible to human mistake.

II. LITERATURE REVIEW

In order to identify two-wheeler riders without helmets, Dahiyaetal. [1] Used present footage and implemented (HOG) Histogram of Oriented Gradients, (SIFT) Scale invariant feature transform, and Local binary pattern (LBP). With this method, the detection accuracy was 93.80%, however the needed time interval was slow at 11.58 frames per second [1]. It offers a two-level method for instantly identifying motorbike riders who are not wearing helmets. In the opening frame of the video, a motorbike rider can be seen. In order to decrease inaccurate predictions, the motorbike rider's head is detected in the second phase, and it is examined to see if the rider is wearing a helmet or not. The procedure is slow since pre-processing methods like HOG, SIFT, and SVM must be applied, even though they are less expensive than previous research. Other work distinguishes bike riders who do not wear helmets and records the number plate of a significant number of defaulters on the database. It also describes a few strategies that are essentially identical to the one provided in this study. Since it employs YOLO to discriminate between helmets and engine cycles, Open ALPR is the system employed for license plate recognition. These two technologies are not cost- effective because they both involve monthly expenses.

Silvaetal presents a local Binary Pattern-based Cross Breed Descriptor for Feature Extraction. [2]. They employed HOG and Hough Transform descriptors for robotized helmet-less motorcyclists to be distinguished from other riders. The results, however, came in later than anticipated. The last few decades have seen a rise in the employment of deceptive techniques like computer vision and artificial intelligence (AI) in smart surveillance at power substations. It can also avoid office equipment problems and professional criminal activity in time and precisely to avoid disasters, in addition to keeping a strategic distance from dull job increased assignments [3].

Another study uses convolutional neural networks (CNN) to recognize ambient objects. Two cutting-edge models for object detection are compared: Single Shot Multi-Box Detector (SSD) with MobileNetV1 and a Faster Region-based Convolutional Neural Network (Faster-RCNN) with InceptionV2. The findings show that, while one model can be used for more accurate object detection, the other is more suited for real-time applications because of its speed. [4].

The newest technologies can assist in identifying motorcycle riders wearing helmets. A solution using Deep Learning and Image Processing technology was put up by Meenu R [5]. CCTV videotape is utilized to determine if a cyclist is wearing a helmet or not. Here, a faster RCNN is chosen since it improves the detection rate of motor cycles. The system is equipped with functions like motorbike, head, helmet, and license plate detection. Using open-ALPR, the vehicle's registration number is recorded, and the local police station is notified.

The use of a vector machine classifier by Kunal Dahiya [6] allowed him to identify bike riders without helmets. This model detects the objects by using circle arc detection. This model processes a frame in 11.58 milliseconds. The initial phase is the detection of bike riders. The second phase involves locating the bike rider's head and classifying them according to whether or not they are wearing a helmet. For the final prediction, the results are collected from successive frames. This approach has the drawback of trying to locate the helmet throughout the full frame, which consumes a lot of processing effort. It may also mistake other items with similar shapes for helmets. It is less effective than the other types because it needs specialized hardware to be set up.

YOLO and Canny Edge Detection are used in Shravan Maliye's solution [7]. The size of the available dataset and the length of training time for the model are the factors that determine the accuracy of the model in this system. As the traffic film is altered, bicycle riders may be seen in every frame. The frames portray two-wheelers as well as other automobiles. This is done using YOLOv3. The system classifies bikers based on whether or not they are wearing a helmet and/or mask after observing them. This also makes advantage of YOLO. This method harvests licence plates and stores them in the specified folder for people who are not wearing a face mask, a helmet, or both.

A system that is based on the research of image processing and deep learning was proposed by K C Dharma Raj [8]. In this case, image processing is utilized to spot motorcyclists who are riding without a helmet. In order to identify license plates, the bike riders are then categorized as either wearing helmets or not. By adjusting the hyperparameters, the number of training examples, and the usage of data augmentation techniques, several trials are run to identify the optimum model for the task. The Support Vector Machine (SVM) technique was applied in this case to distinguish between the riders and the helmet. Convolutional neural networks perform better even with constrained processing resources when the depth rather than the width is taken into consideration.

To locate the bike rider without a helmet, H. Lin [9] used three different techniques. They first utilized a trained RetinaNet model to identify active motor cycles in the frame. The second phase is tracing the motor cycle using surrounding frames. The third step entails determining the quantity, location, and presence of the helmet as the motorbike exits the area of view of the CCTV camera. As a result, the rider can be viewed as either breaking the law or as wearing a helmet.

Convolutional Neural Networks (CNNs) are a method for categorization that C. Vishnu et al. recommended in [10]. CNNs that do automatic feature extraction and classification have recently outperformed previously well-liked methods in a number of challenges. Neural networks can now learn with outstanding precision in the fields of speech recognition, natural language processing, and machine vision thanks to recent advancements in graphics processing units (GPUs). On the foundation of CNNs, all contemporary techniques for object classification, objectdetection, character classification, and object segmentation are constructed.

A fully CNN [11] and a process for post-processing neural network outputs make up the YOLO v3 algorithm. A unique variety of neural network architecture called a CNN was developed with the purpose of digesting grid-like data structures. One distinguishing characteristic of CNNs that is crucial for object detection is parameter sharing. The CNN architecture uses every kernel member at every point of the input, in contrast to feed-forward neural networks, which only ever use one weight parameter. As a result, only one set of parameters—rather thanone set for each site—is learned. There is an adjustment between rapidity and precision when using YOLO in the YOLOv3 AP since RetinaNet learning takes longer than YOLOv3. When using a larger dataset, YOLOv3 may be utilized to recognize objects with an accuracy that is comparable to RetinaNet, making it the ideal option for models that can be trained with huge datasets. This is demonstrated in widely used detection algorithms like traffic detection, where a large amount of data may be used to train the model due to the abundance of images of different cars. YOLOv3 might not be the ideal choice for specialist models for which getting large datasets can be difficult.

III. METHODOLOGY

A. Matching Techniques

There are wide range of algorithms that can be used with differentdata sets, ranging from hand gestures to shapes, objects to hand- written scripts etc. In object/ image detection, each object is separated by distinguished features. The features are characterized by high and low intensity points. In an image this is referred to as "interested" and "non-interested" regions. The most formidable feature of these algorithms is its ability to distinguish featured in a dynamic domain, once trained properly. Below mentioned are some of the methodologies and their comparative study.

Methodologies:

1. Blob Detection
2. Template Matching
3. SURF

A) Blob detection technique: the major advantage of using blob detector over the edge and corner detectors is that it provides a relative and complementary information regarding regions. Blob detection is a methodology that comes after the object has gone through colour and noise reduction with proper morphological operations alongside. Algorithm for blobdetection is as follows:

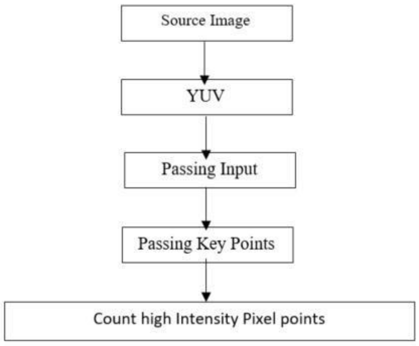
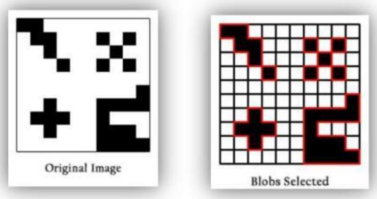


Fig. 1: Blob Detection



B) Template matching: Template matching is one of the techniques of image matching that are like patch. As the name suggests, in this methodology a patch/template is snipped as an extracted feature. Two images are used one as an input domain and other as a reference for the input. Output is usually calculated using following formula:

$$r = \frac{1}{n-1} \Sigma \left(\frac{x - \overline{x}}{s_x} \right) \left(\frac{y - \overline{y}}{s_y} \right)$$

This methodology usually focussed on the searchingand finding methodologies. Template matching dependson correlation factor. Below is the working of template matching using numpy and OpenCV:

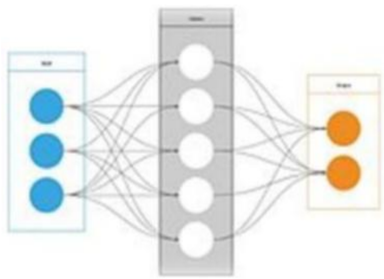


Fig. 2: Template matching

C) SURF feature extraction: SURF stands for Speeded Up Robust Feature. This is a robust feature detector. SURF is relatively a newer and reliable technique. To practice object detection, it makes use of wavelets in response to vertical and horizontal directions. The wavelets are written in vector form as

$$v = \left(\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y| \right)$$

SURF adds a lot of features to improve accuracy and speed.
Considering the element location and highlight extraction strategies talked about above, we have seen that SURF calculation is the probably the best option for picture coordinating issues. In this report, we have examined different significant strategies like Blob recognition calculation, Template coordinating strategy, SURF calculations. We have seen that Blob discovery calculation restricts us to the quantity of motions with

lower precision and slower throughput. Format coordinating methods is somewhat better with moderate unpredictability and precision. In any case, with expanding number of layouts, the effectiveness and the throughput of the calculation is unfavourably influenced. On the side of the announcements, we have put the tried pictures and the relating yields. At long last, SURF calculation is examined with its middle strides alongside the tried pictures and their yields. We have tried the calculation available motions, recognizing objects out of an image, letters, and words from writings and found that it worked with incredible exactness and quicker speed.

COMPARISON	**SURF**	**TEMPLATE MATCHING**	**BLOB DETECTION**
ACCURACY	85-95%	40-50%	10-20%
SPEED	Fast	Intermediate	Very slow
GESTURES LIMIT	Up to 30	**NA**	Up to 5 gestures
INVARIATION (SCALE)	Yes	No	**NA**
INVARIATION (ROTATION)	Yes	Yes	**NA**
COMPLEXITY	More complex	Less complex	Least complex
CONSTRAINTS	Works well for all image	Background colour must be different from text	Image must be grayscale

B. Comparitive Study of Different Object DetectionModels

Yolo v5 : YOLO has dominated the field for a long time. We had a big breakthrough in May 2020. updated two improved versions of YOLO appear one after another others. One was YOLOv4, which has been in development for a long time. The other is his newly released YOLOv5. This was not the author of the traditional YOLO series The new version sparked some controversy, Skipping that, the v5 model showed decent performance. It has improved performance compared to its predecessor. However, YOLOv5 had many advantages engineering. A much appreciated change is the usagePython language apart from C in the previous versions. This makes the installation and the integration along with IoT devices very easy. Additionally, the community of PyTorch is larger. This means that PyTorch will do this for you. Receives more posts and has great growth potential future.

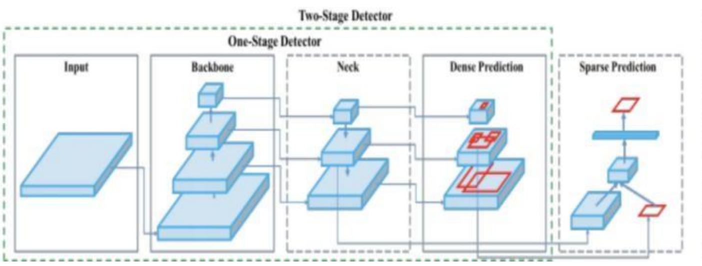


Fig. 3: Yolo v5 model architecture

SSD Mobile Net: SSD is known as single-shot detector. It does not have a delegated region proposal network and predicts the boundary boxes and the classes directly from feature maps in one single pass. To improve accuracy, **SSD** introduces: small convolutional filters to predict object classes and offsets to default boundary boxes.

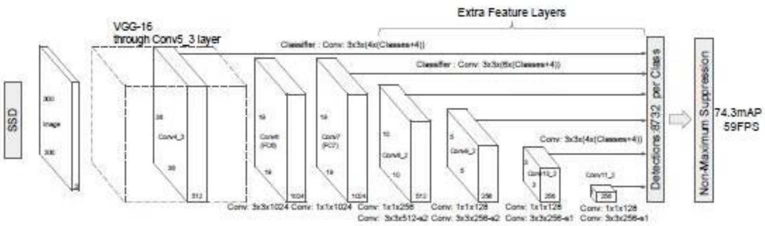


Fig. 4: SSD Mobile Net architecture

EfficientDet D0 512x512: Before moving on to the contributions of EfficientDet, we will talk about the design of Efficient Net since it serves as the foundation for the architecture of EfficientDet. ConvNet structural scalability was a goal of Efficient Net. EfficientNet set out to build the procedure to automatically scale ConvNet-model-architectures.

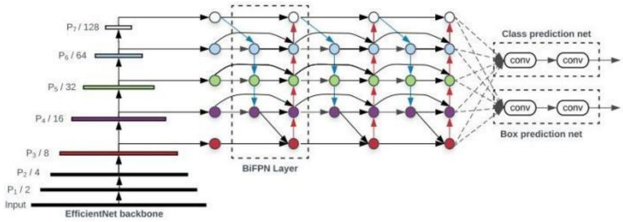


Fig. 5: EfficientDet architecture

Name	Speed (ms)	COCO mAP[^1]	Outputs
ssd_mobilenet_v1	30	21	Boxes
ssd_mobilenet_v2	31	22	Boxes
CenterNet Resnet 50	27	29.5	Boxes
EfficientDet D0	39	33.6	Boxes
YOLOv3	29	51.5	Boxes
Faster_rcnn_inception_v2_coco	58	28	Boxes

Name	Speed (ms)	COCO mAP[^1]	Outputs
YOLOv5	28	37.6	Boxes

IV. PROPOSED WORK

TensorFlow Version: 2.3.0

TensorFlow has a long range of benefits that much transcend its fame compared to a few of its top rival AI packages. Some of the characteristics that give it this powerful advantage include the following:

- Your TensorFlow model can be examined using theTensorBoard Graphs dashboard. You may rapidly assess your model's structure and evaluate whether it follows the necessary design by using a conceptual graph of it.
- Rapid feature extraction is done by Google, and it ensures that the TensorFlow pipeline receives regular library changes. All of the computational layers in your ML model include weights and biases that are constantly being changed while it is being trained.
- Within the TensorFlow program's execution, catastrophic occurrences may cause the model training processes to stop. A dedicated dashboard is offered by TensorBoard to help troubleshooting any kind of model mistake easier.

This version is specifically chosen to aid the application in train newer models via transfer learning and that too efficiently. The newer TensorFlow 2 helps us in instantly converting the model trained into the "lite" version which makes it compatible with mobile devices and yet has a wider implementation in the future of this project.

Model Selected for project: Yolo v5.

Each of the model were effective in the necessary helmet detection application, but the YOLOv5 was the best model for theapplication of real-time deployment due to the combination of its accuracy and speed. The other models listed are also quite good and have various use case scenarios. Knowing there is Yolov7 which is a more efficient model than the Yolov5, yet this choice have been made keeping in mind that TensorFlow not only ships with object detection algorithms but also ways in which detection of the objects could be put to good use. For Example, a simple python code with optimal use of API's provided by TensorFlow could even help us in tagging every object in the frame and even calculating speed relative to the near-by objects.

The classifier inside the model that is being used is a combination of Convolutional Neural Nets and Dense networks. Neural Nets have the property, "Better the data, Better the job done". After trying for weeks, a suitable dataset has not been identified or free as well as paid services. There are datasets available but the images, inside it, are not the portraying the Indian traffic. The core of the application lies inside the data and if we are not ableto identify vehicles, how will the application's penalization system work. Hence, it has been decided by the team that adataset will be prepared for the application and it would be comprising around 400 images for starters and will be incremented upon if required.

Machine Chosen: A local machine with decent processing powerin case of CPU as well as GPU.

We will be training two models for the application which will be performing completely different tasks. For the first prototype of the application both the models will be trained via transfer learning on a local machine, so that the dataset requirements can be altered at any time. Training on a local machine will be aiding us in the documentation part and since we have limited space on the cloud, we have made the choice of local machine. The local machine that will be used will be having an i5-10300H as CPU, 8 gigs of RAM, 4GB Nvidia GTX 1650 Ti as GPU and a dedicated disk drive of 1000gbs. Such high-end configuration is chosen because we might need to train a single model multiple times for the efficiency.

Workflow:

- Create a library of videos showing motorbike riders wearing and not wearing helmets. This dataset should be big enough to provide the model plenty of training data. We can either create our own movie or amass clips from other internet video sharing websites like YouTube.
- To indicate whether or not the images in the dataset show people wearing helmets, use a tool like LabelImg or RectLabel. At this crucial stage of supervised learning, the model gets the ability to distinguish between cyclists who are wearing helmets and those who are not.
- Make training and validation sets from the dataset. After the model has been trained using the training set, its performance will be assessed using the validation set. Validation frequently employs 4:1ratio for dividing the dataset into training and validation sets.
- Describe the deep learning model's architecture that we will be utilising for this project. This might either be a custom model that you develop from scratch or a pre- trained model that you adapt for your specific objective. One popular pre-trained model for object recognition is the Single Shot MultiBox Detector (SSD) architecture.
- Install TensorFlow or PyTorch or other essential deep learning libraries on your computer. These libraries offer the tools necessary for developing and improving deep learning models.
- Preprocessing of the dataset's images should include scaling, normalising the pixel values, and performing any other necessary corrections. This ensures that the photographs are in a format that the model can work with easily and reliably.
- The preprocessed images and the labels that go with them should be loaded into memory using a data loader. After collecting them in batches from the disc, the data loader loads collections of images and labels into memory in a manner that the model can comprehend.
- Train the model on the training set while utilising a loss function and an optimizer to update the model weights. According to the loss function, which measures how well the model is doing, the optimizer updates the model weights to reduce loss.
- Track the model's training progress using metrics like recall, accuracy, and precision, and adjust the hyperparameters as needed to improve the model's performance. Hyperparameters are parameters that affect how the model learns, such as the pace of learning.
- To gauge how successfully the trained model generalises to new examples, evaluate it on the validation set. This step is essential for evaluating the model's effectiveness and pinpointing areas that need improvement.
- Expand the quantity of the training set using methods like data augmentation, then retrain the model to get better results. In order to give the model brand-new examples that it has never seen before, data augmentation entails randomly altering the images in the dataset.
- To make predictions on new photos or videos in the future, store the trained model weights to disc. We

can use the model for inference on new data by saving the model weights rather than retraining the model from scratch.

- Validate the model's accuracy by providing it with fresh photos or videos, then comparing the outcomes to the labels on the real world data. This stage is essential for evaluating the model's performance in the actual world and finding any potential problems.
- Adjust the model as necessary to increase precision and minimise false positives and false negatives. In order to increase the model's performance on a particular job, fine-tuning entails changing its hyperparameters or architecture.

V. CONCLUSION

Due to India's rising economy, two-wheeler have replaced cars as the main form of mobility. According to estimates, there are currently roughly 40 million two-wheeler in India. India now has the most motorized two-wheeler per capita in the entire globe. According to data from the Transport Ministry and a Times of India study, as of 2016, 28 two-wheeler riders died on Indian roads every day as a direct result of failing to wear helmets.

This initiative aims to reduce accidents due to improper helmet use. It also confirms if the law has been broken or not. It keeps a record of the violators' images. This project is a road safety application for detecting helmet violations. We have compared and discussed different kinds of techniques for image processing, object detection and feature extraction. This paper shows a work for detecting two wheeler defaulters. Feature extraction techniques like blob detection, Surf and template are compared on various parameters. According to this comparison feature extraction technique would be selected for further data extraction from the custom dataset containing videos of traffic. Further techniques to process images and detect objects are discussed and compared. TensorFlow 2 model would be used for the implementation purpose. It contains image detection model like YOLO v3, YOLO v5, SSD mobile net etc. YOLO v5 has been selected for fast and accurate results. It analyses the videos by taking frames and then identify object by differentiating background from the image. This the most important task for converting dataset videos to processed images. The sequence flow for the proposed methodology is also defined in this report and the mechanism of different units are shown in collaboration diagram. In future, the main focus would be on implementing the strategies that have been discussed in this paper.

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