Optimizing Helmet and Vehicle Number Plate Detection with Advanced YOLO Models

A Thesis Submitted

In Partial Fulfillment of the Requirements for the Degree of

MASTERS OF TECHNOLOGY
IN
Data Science

Submitted by

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23/DSC/28

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JUNE, 2025

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ACKNOWLEDGEMENT

I wish to express our sincerest gratitude to Dr. Shweta Meena for his continuous guidance and mentorship that she provided me during the project. She showed us the path to achieve our targets by explaining all the tasks to be done and explained to us the importance of this project as well as its industrial relevance. She was always ready to help us and clear our doubts regarding any hurdles in this project. Without her constant support and motivation, this project would not have been successful.

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CANDIDATE'S DECLARATION

I, Anchal Gautam, Roll No –2K23/DSC/28 students of M.Tech (Data science), hereby certify that the work which is being presented in the thesis entitled "Optimizing Helmet and Vehicle Number Plate Detection with Advanced YOLO Models" in partial fulfilment of the requirements for the award of degree of Master of Technology, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during period from Jan 2025 to May 2025 under the supervision of Dr. Shweta Meena.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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I hereby certify that the Project Dissertation titled "Optimizing Helmet and Vehicle Number Plate Detection with Advanced YOLO Models" which is submitted by Anchal Gautam, Roll No – 2K23/DSC/28, Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

The goal of this project is to enlarge dependable and structured system for identifying number plates using YOLOv5 and YOLOv8, two popular iterations of algorithm for identifying objects YOLO ,you only look once. For applications like automatic tolling, traffic tracking, and the authorities, this system's ability to automatically recognize and extract license plates from images of two wheelers vehicle is important.

A specially set up dataset of labelled vehicle images is used to train the YOLOv5 and YOLOv8 models for project. The models are then assessed and contrasted according to their durability in different environmental conditions, detection accuracy, and diagnosis speed.

Also, using optical character recognition ,OCR to fetch text from recognized license plates enhances the effectiveness of the system. The comparison's result show that YOLOv8 is more beneficial for real-time performance than YOLOv5 because of its improved architecture, which provides higher accuracy and faster inference rates. The effectiveness of DL techniques in solving problems related to license plate recognition is mentioned in this work, which offers a workable and scalable solution for automated transportation systems.

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Chapter 1

INTRODUCTION

In order to enable important features like automated trouble collection, parking control, business regulation, and law enforcement, license plate identification is the main part of contemporary intelligent transportation systems [1]. delicacy, inflexibility, and real- time performance have been issues for traditional number plate recognition styles, particularly in a variety of vehicle types and downfall situations [2].

These restrictions can now be more successfully handled thanks to developments in deep knowledge and computer vision. The capacity of the YOLO ,You only look once formerly object identification algorithm to descry objects in real time by coincidently detecting object classes and their related bounding boxes inside a single image has made it extremely popular.

Among the different performances of YOLO, YOLOv5 and YOLOv8 have drawn a lot of attention due to their robust functionality and simplicity of use. The delicacy, recovering speed, and architectural optimization of YOLOv8 are superior to those of YOLOv5, which is formerly fairly effective [3]. With its advanced features, YOLOv8 provides hastily conclusion and better discovery capabilities, which makes it the perfect option for real- time operations where performance is vital.

The performance and performance comparison of YOLOv5 and YOLOv8 for vehicle number plate discovery in prints is the main thing of this exploration. The implementation of both models will be estimated in related to severity under colorful environmental circumstances, conclusion speed, and discovery delicacy after they've been trained using a particular dataset of annotated vehicle prints [4]. In order to ameliorate the system's overall effectiveness and avail, it'll also use optic character recognition, or OCR, to prize textbook from the honored license plates.

In order to give precious perceptivity into the performance of colorful YOLO designs in practical operations inside intelligent transportation systems(ITS), the primary thing of this exploration is to present a comprehensive comparison between YOLOv5 and YOLOv8 for vehicle number plate discovery. In order to support essential functions like automated tolling, parking operation, business regulation, and public safety surveillance, number plate recognition is an essential element of contemporary ITS.

Road safety, increased law enforcement, and more effective business operation are all greatly impacted by accurate real- time number plate discovery. multitudinous vehicle types, shifting illumination, bad downfall, high business, and the variety of number plate forms in colorful locales are some of the difficulties this duty brings.

License plate recognition has authentically depended on traditional pictures processing methods like template matching, boundary detection, and contour testing. Although these techniques worked well in controlled settings, but they frequently had trouble with real-world variances such shifting plate orientation, obstructions, and distorted images. Additionally, for them to work well, they required so much manually performed to extract features and parameter optimization [7], [14]. These drawbacks pointed the growing demand for more sophisticated, automated, and scalable methods.

Image analysis and recognition have made huge strides in current years due to of object identification models using deep learning, especially in YOLO family [8], [13]. YOLO is a good object detection framework that can locate and identify many objects in a single forward pass, providing significant speed and accuracy gains over traditional methods [9]. It is ideal for applications such as vehicle license plate detection, for which quick analysis of photos or video streams is important for prompt decision making, as its architecture is particularly developed for real-time analysis.

Many versions of first YOLO algorithm have been made, each of that has improved computational efficiency and accuracy detection [10], [12]. Because of its excellent performance, adaptability, and simple in use, YOLOv5 has become a well-liked and dependable model among these [11], [15]. It has been effectively used in a no. of fields, including as license plate recognition, vehicle tracking, identification of pedestrians, and facial recognition.

Yolov8, it is the most recent version, improves network even more by offering faster training times, enhanced generalization across a variety of datasets, and larger detection accuracy.Because of these enhancements, YOLOv8 is especially well-suited for real-time vehicle license plate recognition, where operational efficacy depends on high-speed image processing.

CHAPTER 2

LITERATURE REVIEW

Shuai Chen etal.(2022) found out the difficulties of relating helmet use among riders using upstanding imagery taken by unmanned upstanding vehicles(UAVs) by proposing a new discovery fashion that combines model- grounded high- resolution restoration, a motor- grounded spatial focus medium, and the YOLOv5 print classifier. The issue arises from rudiments including stir blur in upstanding prints, large size changes, and small confines of asked issues, which lead to a weak conception of current models and low delicacy in discovery. The authors address these problems by creating a graduation- typemulti-attention networks for thing identification, which is intended to reduce loss of data, completely prisoner visual features, and make sharing of information and linking across categories easier.

Sunil Kumar et al.(2023) punctuate the growing significance of vehicle discovery and shadowing in sustainable intelligent transportation systems for managing real- time trace business inflow. still, being deep literacy- grounded approaches continue to face challenges arising from variations in vehicle sizes, occlusions, and dynamic business conditions. To address these challenges, the authors propose a smart and effective result that employs YOLOv5 for vehicle discovery, achieving of over to 140 FPS. In order to efficiently follow and read machine movements in presently, this discovery is also coupled with Deep Simple Online and Realtime Tracking(Deep SORT).

Wojciech Lindenheim- Locher et al.(2023) concentrate on original stage of the 3D drone shadowing challenge, specifically precise discovery related to drones in pictures captured by a multi-camera system. The study employs the YOLOv5 deep literacy model, trained and estimated at colorful input judgments using real multimodal data comprising accompanied videotape sequences alongside stir prisoner ingormation as dependable ground verity reference. Discovery bounding boxes are find out grounded on the 3D position and exposure of an asymmetric cross mounted on top of drone, deposited at a given distance from its center. The arms of this cross are linked using stir prisoner labels.

The difference in distance between the center points of linked drones and their affiliated factual references, acclimated for false positive and false negative rates, is a new evaluation metric designed for 3D shadowing delicacy that goes beyond the traditional mean average perfection(chart) metric. likewise, both the training and evaluation stages made use of pictures produced in the AirSim script frame.

Ju Han et al.(2023) concentrate on helmet identification in the structure sector, where it's delicate to achieve quick discovery using being ways due to the demand for high- resolution picture transmission. They created a super resolution(SR) reconstruction module to ameliorate the picture quality earlier discovery in order to deal with this. A multichannel medium for attention is included in this module to enhance graphical rooting of features.

In order to minimize data loss and reduce grade confusion, they also give a unique Cross Stage Partial(CSP) module grounded on YOLOv5. Experimental tests have verified the effectiveness of the suggested strategy.

Deep literacy- grounded helmet recognition algorithms are the main focus of Weipeng Tai et al.(2023), who want to enable continuously recognition and shadowing of contraventions, similar as failing to wear helmets. still, precise helmet discovery is made more delicate by everyday problems like bad rainfall and mortal error. blights and dropped discovery trustability are constantly caused by issues including camera shaking and head occlusion. The work suggests a new system named DAAM- YOLOv5 to overcome these problems. By using Mosaic9 data addition, which raises the mean Average Precision(chart) in delicate situations, this system enhances the dataset in a variety of circumstances.

Yixiao Zhang et al. stress the significance of vehicle identification and localization in systems that drive autonomously in their 2024 study. In grueling circumstances, classical discovery ways are constantly limited by changes in object scale, occlusions, and lighting, all of which lower discovery delicacy and thickness. The authors suggest a fashion that combines binocular vision and YOLOv5(You Only Look formerly, interpretation 5) to overcome these problems. This system makes use of two cameras to contemporaneously take filmland from colorful angles, enabling more accurate depth estimate by comparing the differences across the two pictures.

According to Jianfeng Han et al.(2024), effective real- time observation is necessary to insure helmet compliance at construction locales in order to avoid injuries. After considering a number of options, they decided to integrate the Ghost Module into a YOLOv7- grounded armature in order to more use it and satisfy this need. This enhancement results in a more effective design that improves factual- time performance by producing further point maps with smaller direct operations. also, after assessing several attention styles, they added SE(Squeeze- and- Excitation) blocks, which helped the model concentrate more efficiently on material picture data. In order to meet safety monitoring conditions, the attendant system maintains outstanding delicacy in discovery while achieving enhanced runtime effectiveness.

Maged Shoman et al.(2024) combine Yolov8 object identification system with deep convolutional generative adversarial networks ,DCGANsto present a unique system for relating helmet operation breaches among motorbike riders. The thing of this fashion is to ameliorate the delicacy of the present helmet violation discovery systems, which calculate substantially on mortal examination and constantly have inaccuracies. Indeed in situations with several riders, the system achieves excellent delicacy in detecting helmet contraventions by using a sizable dataset made up of both factual and artificial prints to train the model. Data addition styles are used in confluence with simulated pictures produced by DCGANs for enrich the training data in order to further ameliorate model performance in real- world conditions. Resolving the problem of class difference is given special attention.

CHAPTER 3

PROPOSED METHODOLOGY

3.1 Helmet and Number Plate Detection:

In video footage, helmets and license plates are detected using an object finding way that identifies these details within individual video frames. After detecting a helmet, the algorithm performs helmet classification to decide whether it's being worn. To upgrade visual clarity, bounding boxes are drawn around detected objects, indicating whether a helmet is present or absent. The system operates in real time, recycling frames as they're captured and optimizing for dynamic surroundings. It displays the reused video and allows the user to break playback by pressing the" Esc" key, enabling interactive control.

also, algorithm efficiently handled computationally to preserve smooth video processing. In summary, this system effectively detects, classifies, and visualizes helmets and license plates in videos, furnishing real- time information with high accurateness.

This study employs a methodical systematized to elaborate good system for detecting license plates and helmets. After an expansive data collection phase, a different dataset of annotated images representing real- world conditions is assembled.

Data preprocessing including normalization, resizing, and augmentation is performed to prepare the dataset, with an emphasis on equalizing accuracy and computational productiveness. Transfer learning plays a crucial part in fine- tuning a namedpre-trained deep learning object discovery model using the labeled dataset, conforming it specifically to the task conditions.

To help overfitting, the training process precisely partitions the dataset, adjusts hyperparameters, and continuously validates performance. Post-processing ways are applied to enhance detection accuracy, while evaluation metrics similar as precision, recall, measure the model’s efficiency.

Central to this study is the flawless integration of the trained model into real- time systems, fastening on optimizing speed and efficiency. The model undergoes rigorous testing and validation to insure robustness across colorful surroundings and scenarios. Through iterative fine- tuning and thorough documentation, the system's reproducibility and scalability are assured, contributing to advanced road safety and advancements in intelligent transportation systems.

The entire network — including the spotting head, Region Proposal Network(RPN), and backbone is optimized using the labeled dataset. Transfer learning amplify pre-trained weights derived from image classification tasks. The detection head, structured as a completely connected network, refines bounding box coordinates and classifies proposed regions into predefined divisions similar as helmets and number plates.

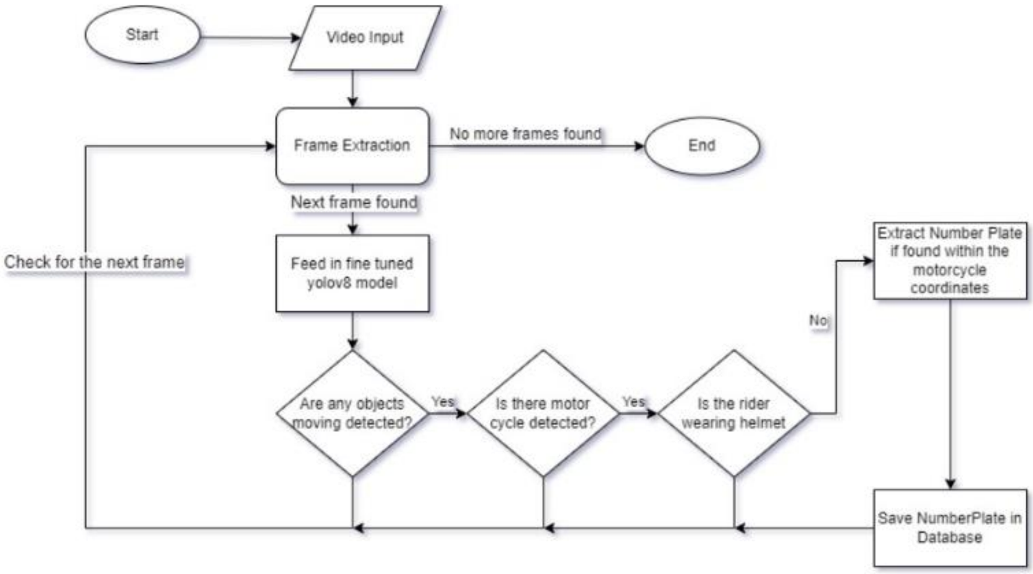

Fig. 3.1 flowchart

3.2 YOLOv5 and YOLOv8 Architecture design

The YOLO object identification framework comes in two versions, YOLOv5 and YOLOv8, each of which offers high-speed real-time detection abilities but varies in design, performance, and flexibility. Because of its great accuracy, quick inference speed, and user-friendly architecture, YOLOv5, created by Ultralytics and implemented using PyTorch, has become very popular. For object detection in photos, movies, or live webcam streams, it offers simple settings. Users can select a model that best suits their computing capabilities and preferred trade-off between speed and accuracy thanks to YOLOv5's availability in four different sizes: small, medium, large, and extra-large.

YOLOv5 model's applicability is significantly greater than that of typical pre-trained versions since it allows users to train customized models using their own datasets. Because of its adaptability and availability of pre-trained weights (like those learned on COCO or other specialized datasets), YOLOv5 is a well-liked option for a variety of real-time detection tasks, particularly those where computing efficiency is a top concern. YOLOv5, which is implemented in PyTorch, is a good solution for both novice and expert users since it allows developers to swiftly expand and alter the model to fit certain requirements.

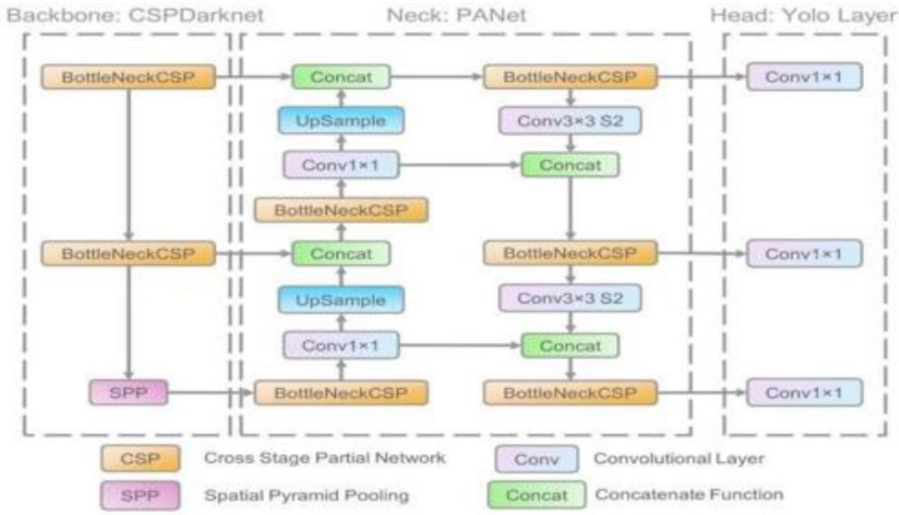

Fig. 3.2 Yolov5 Model Architecture

In contrast, YOLOv8 represents the rearmost development in the YOLO series, offering significant advancements over former versions similar as YOLOv5. While YOLOv5 set a strong standard for real- time detection, YOLOv8 introduces an improved architecture, advanced optimization ways, and a more streamlined framework that significantly improve both speed and accuracy.

Integrated within the Ultralytics Python package, YOLOv8 not only supports detection but also provides comprehensive tools for model training, evaluation, and export. Its further modular design offers users lesser flexibility to customize training workflows and import models in colorful formats like ONNX and TensorFlow, enabling flawless deployment across distinct platforms.

Object identification algorithm You only look once version 8 was created by Ultralytics and its aimed to carry out tasks like object detection, image segmentation, and division. To work on numerous architectural and functional increment, it builds upon advantages of earlier duplications of YOLO algorithm.

The YOLOv8 Unified Model Architecture's salient features include YOLOv8 is a framework that combines object finding, instance segmentation, and category.

1. Increased Accuracy More performance brought about by advanced training forms and a more worldly-wise framework.

2. Efficiency and Speed: High detection speeds are optimized for real-time applications.

3. Flexibility: Model sizes range from YOLOv8n (nano) to YOLOv8x (extra-large), supporting a range of application cases.

A multiple of computational models are implemented by YOLOv8, including: Convolutional Neural Networks (CNNs):

Convolution Operation: After a filter is sliding across the input image, the spatial connections among the pixels are captured.

$$(f * g)(x) = \int_{-\infty}^{\infty} f(t)g(x - t)\, dt$$

where functions being convolved are f (t) and g(t).
x: the variable used to assess the convolution's outcome.
Pooling Operations: Max Pooling or Average Pooling lower the dimensionality of t feature maps which convolutions extract.

$$\text{Max Pooling}(x, y) = \max_{i,j}((x + i, y + j))$$

mAP (mean average precision):

Precision: Its measure shows percentage of accurate detections (excluding false positives).

$$Precision = TP/(TP + FP)$$

Recall: This measure, which excludes false negatives, shows the percentage of real items that the model successfully identified.

$$Recall = TP/(TP + FN)$$

where:
True Positive (TP) and False Positive (FP) True Positive (TP) True Negative (TN)
The 80 pre-defined classes in the models in which Ultralytics provides, which were trained on COCO, (common items in context) dataset, range from animate objects like bicycles, vehicles, motorbikes, traffic lights etc. to animate objects like people, birds, cats, and dogs.

The YOLO family has evolved through multiple versions, including YOLOv4, YOLOv5, YOLOv6, and YOLOv7 [6]. In 2023, Ultralytics introduced YOLOv8, as illustrated in Figure 3. Unlike YOLOv5, YOLOv8 incorporates a new C2f module in its backbone architecture, which is based on the Cross Stage Partial (CSP) structure. This CSP-based design improves the model's learning capability while lowering computational demands. The C2f module [6] consists of two convolutional layers and n bottleneck blocks, connected using split and concatenation operations. Most of the backbone remains similar to YOLOv5, and the final layer of the backbone in YOLOv8 includes the SPPF module [6].

YOLOv8 is distinguished by its systematic single-stage architecture, making it highly effective for real-time object identification tasks. Below is here brief summary of main parts:

Backbone Network: It is core of the model is a Convolutional Neural Network (CNN) backbone, commonly revised version of darknet (like CSPDarknet53). This backbone abstracts multi-level features from the input image, providing a detailed and robust representation for detecting objects.

Neck Network: Some variants of YOLOv8 incorporate a neck network, which enhances the feature maps obtained from the backbone by merging information across different scales. This process generates a richer and more unified image representation that captures details at different resolutions.

Head Network: It is the processes refined feature maps (from the backbone and neck) to perform the last object detections. It’s usually consists of multiple convolutional layers followed by fully connected layers which figured out bounding box coordinates as well as classify detected objects into specific categories.

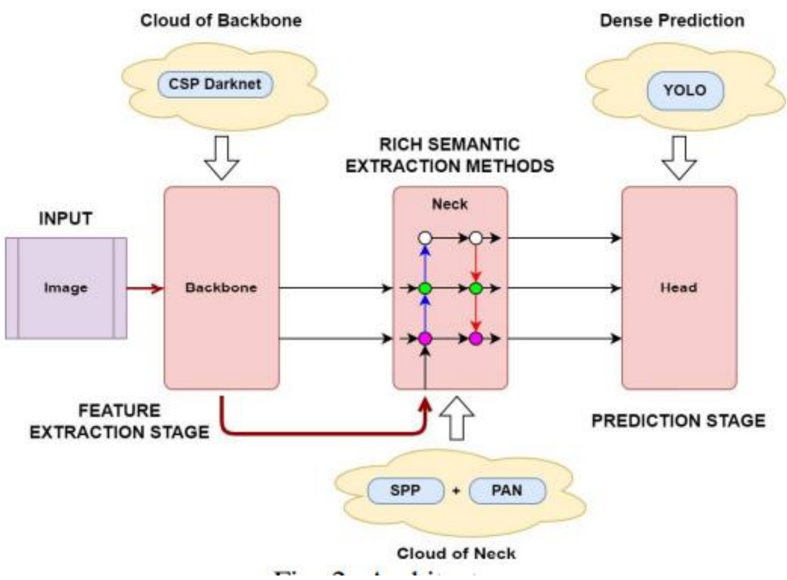

Fig. 3.3 Yolov8 Model Architecture

Hence, YOLOv8 processes an input image by first passing it through the backbone network for to extract features, alternatively enhancing these characterstics via neck network, and ultimately using head network to generate bounding box predictions and classify detected objects.

CHAPTER 4

EXPERIMENTAL_SETUP

4.1 The test environment:

Hardware configuration

Workstation: HP using Processor of intel-core i7, 7^{th} generation with RAM 64GB

Software environment

Using operating system like window 10 and in Programming language using Python.

Libraries utilized

NumPy – for efficient numerical operations and Scikit-learn for supporting ML tasks

4.2 Dataset used:

The Helmet and number plate detection dataset consists of 942 images capturing road traffic scenes of India, featuring riders and their powered two-wheelers from kaggle. This dataset is split into a training set with 800 images and a validation set containing 142 images.

4.3 Implementation procedure:

The images are taken from various locations throughout India, representing diverse lighting conditions, different types of road infrastructure, and varying weather scenarios. Each image is paired with an annotation file in standardized format, that labels in the following categories:

0: Number Plate

1: Face without Helmet

2: Face with Proper Helmet

3: Face with Improper Helmet

4: Rider

Save this file as data.yaml in the root of the dataset folder.

Place all .jpg or .png images in images/train/ and images/val/.

Place the corresponding .txt files with YOLO annotations in labels/train/ and labels/val/.

Verify data.yaml is correct.

Train with YOLOv5 or YOLOv8.

Reads all images from a source folder then Splits them into train/val sets (default: 80/20).

opies both images and corresponding .txt label files to:

images/train/, images/val

labels/train/, labels/val

Understanding class groups—the no. of images per category is essential. Since the dataset may be imbalanced (with uneven numbers of images across classes), tailored training strategies might be necessary to make the model performs effectively across all helmet usage categories.

A.Training

A total of 800 images from the described dataset were utilized to train a pre-trained YOLOv8 and YOLOv5 model. dataset features two wheelers riders both wearing or not wearing the helmet.

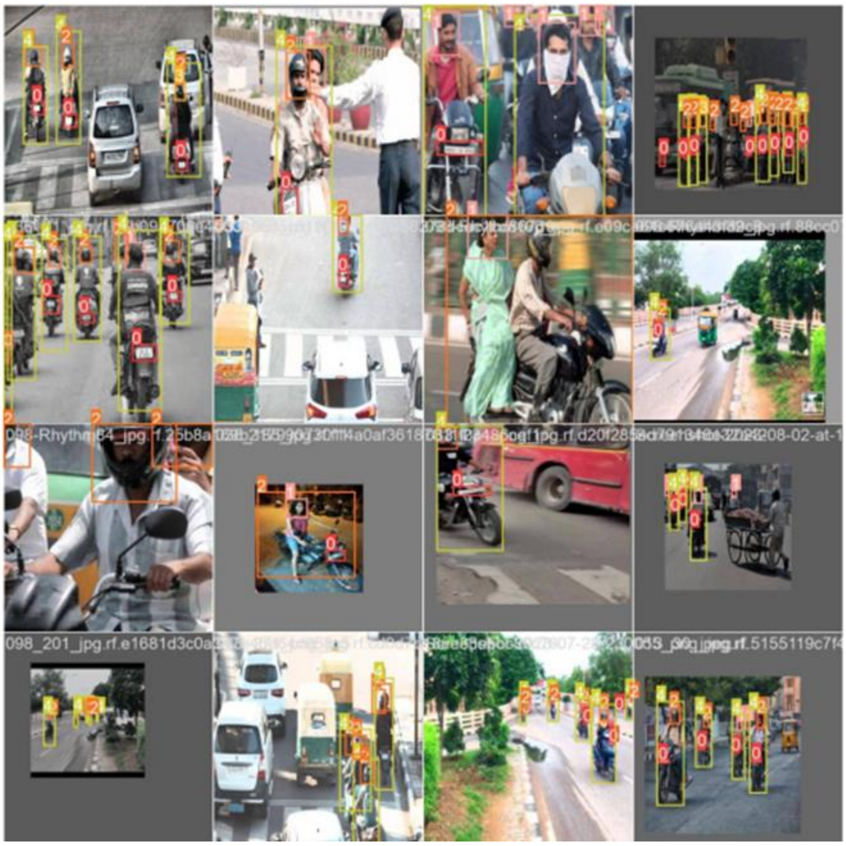

Fig. 4.1 Train images

To enhance the model’s generalizability and aoid the overfitting, photos size was fixed throughout training. The model was trained using specific parameters, initially running for 100 epochs; however, preferable performance was observed at the 48th epoch.

To reduce redundancy and minimize overfitting, the following training configuration was chosen as optimal:

epochs = 100: Defines the total no. of times the entire training dataset is passed through the model for training and validation.

batch = 16: Specifies the no. of images processed in each training iteration.

imgsz = 640: Sets the resolution to that all training images are resized earlier being input into the model.

optimizer = SGD: shows optimizer algorithm used for updating model weights, here stochastic gradient descent (SGD).

lr = 0.01: starting learning rate controlling weight’s size updates during training.

momentum = 0.937, weightdecay = 0.001: Additional hyperparameters paired with SGD to enhance training stability and convergence.

B.Testing

To assess the YOLOv8 and YOLOv5 model's generalization and suitability for real-world use, testing was performed on unseen images that were not part of the training and validation sets. single test picture was used to analyze the model’s processing speed across different stages:

- **Pre-processing (0.6 ms/image)**: here in this phase includes operations such as resizing pf photos and normalization. The quick pre processing time reflects proper preparation of input informations.
- **Inference (16.3 ms/image)**: In this crucial step, image which is pre proceesed is fed through the YOLOv8 and YOLOv5 model to produce object identifications.

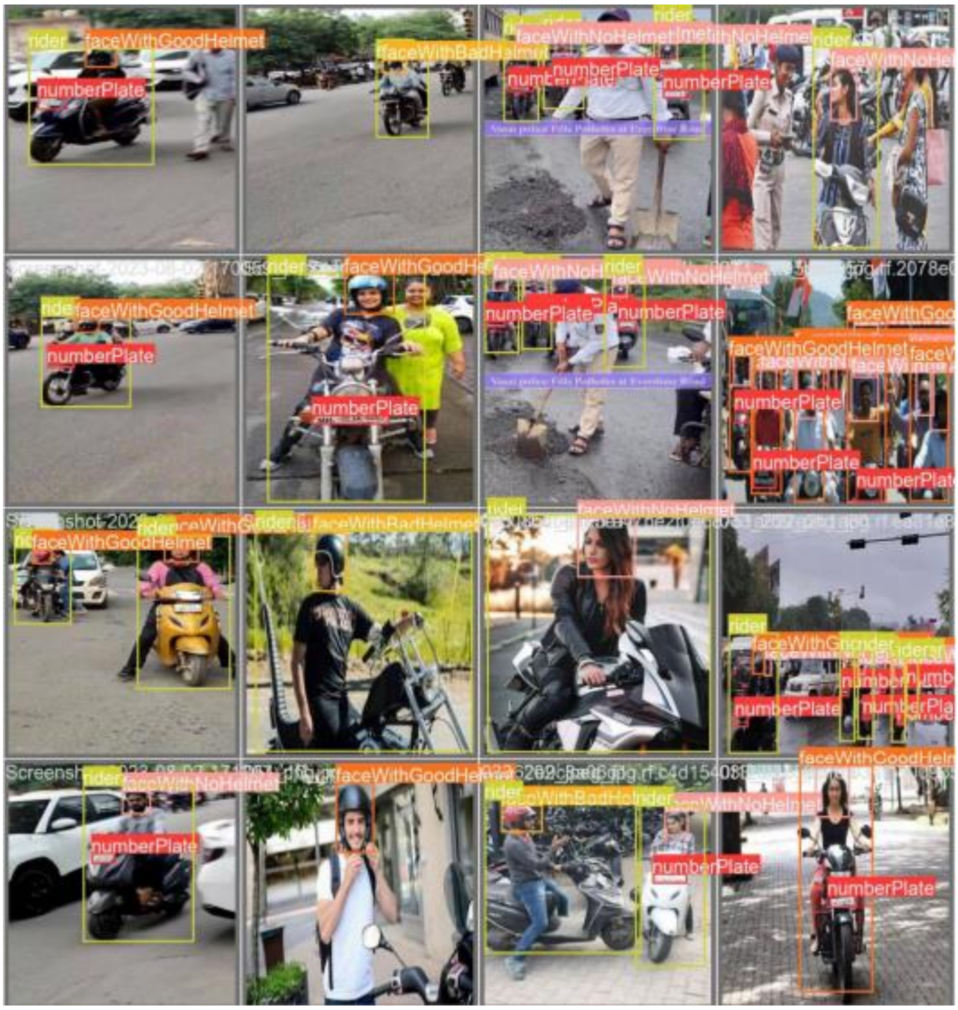

Fig. 4.2 Validation images

The inference speed closely matching validation speed suggests consistent performance among controlled test conditions and real-world usage.
Post-processing (from 98.3 ms to under 2 ms): The duration of this step depends on picture's complexity and specific tasks involved. It generally includes interpreting model's output and applying non-maximum suppression,NMS to filter out duplicate or overlapping bounding boxes.

ExperimentalResults

The model's effectiveness was assessed using 142 validation images, applying evaluation metrics like mean average precision (mAP), which measures both the accuracy of things identification and the precision of bounding box localization. This validation helps in detecting potential overfitting. Based on the evaluation, the following performance metrics were obtained:

Overall mAP of 0.676: This reflects a strong overall object detection capability across all categories, indicating solid model performance.

High mAP for riders (0.9), license plates (0.736), and good helmets (0.745): The model demonstrates strong accuracy in identifying key targets, particularly riders and safety-relevant elements.

Relatively fast inference time: The model processes images efficiently, making it well-suited for real-time analysis.

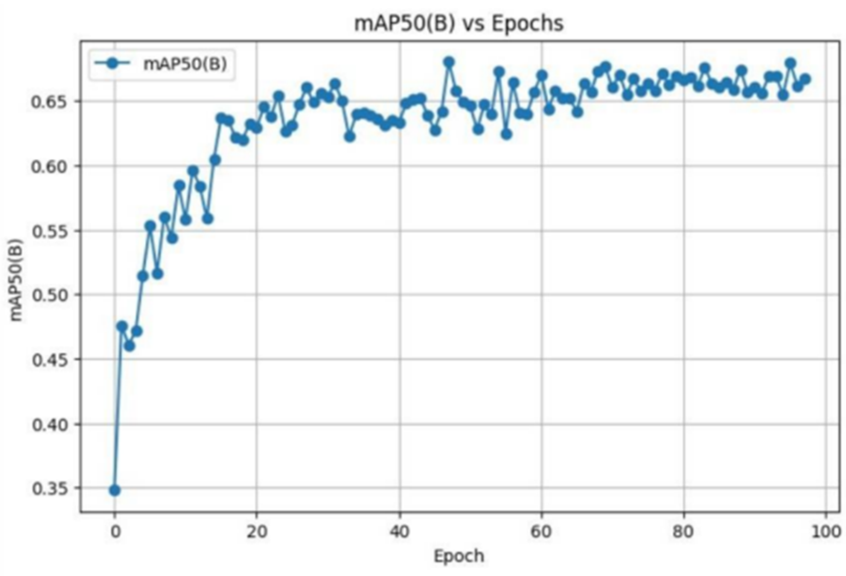

Fig. 4.3 Epoch VS Precision

CHAPTER 5

RESULTS AND COMPARISON

The precision-recall curve is used to determine the precision at IoU.

$$\mathrm{mAP@50} = \frac{1}{C}\sum_{i=1}^{C}\mathrm{AP}_i^{50},$$

The formula is as follows: AP50i is the Average Precision at IoU 0.5 for class I, and C is is total no. of classes. The precision values for each class are averaged across a range of IoU thresholds to determine the mAP from IoU 0.5 to 0.95 with a step of 0.05. The precision-recall curve is used to determine the precision at each IoU threshold.

$$\mathrm{mAP@50{:}95} = \frac{1}{C}\sum_{i=1}^{C}\frac{1}{10}\sum_{t=50}^{95}\mathrm{AP}^t{}_i,$$

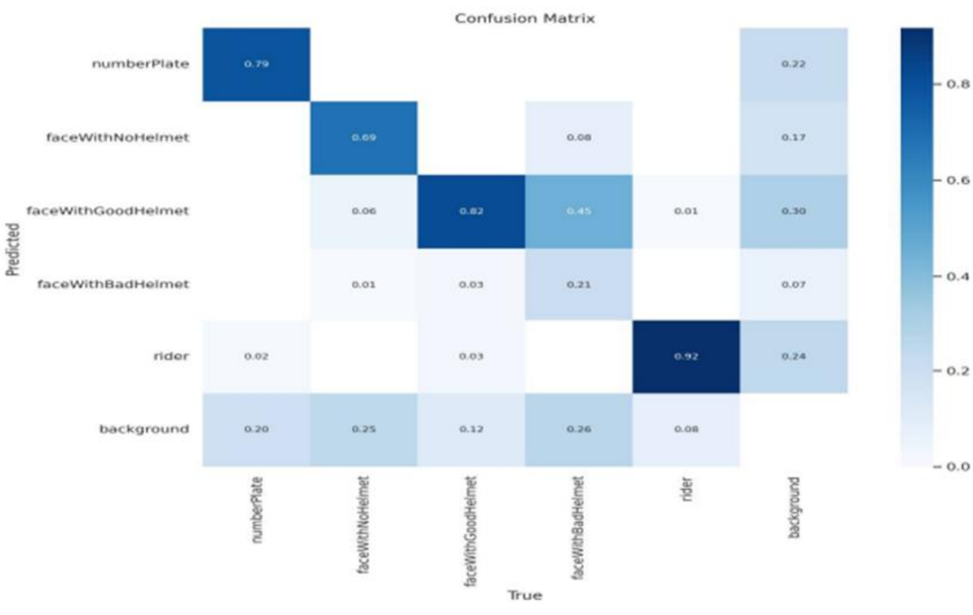

Fig. 5.1 Confusion_matrix

Training and Validation Loss: training loss curve (in blue) shows a compatible reduction across epochs, demonstrating so model is effectively learning from training data. Similarly, validation loss curve (in green) also exhibits a downward trend and indicating best generalization and suggesting that model is not overfitting to the training set.

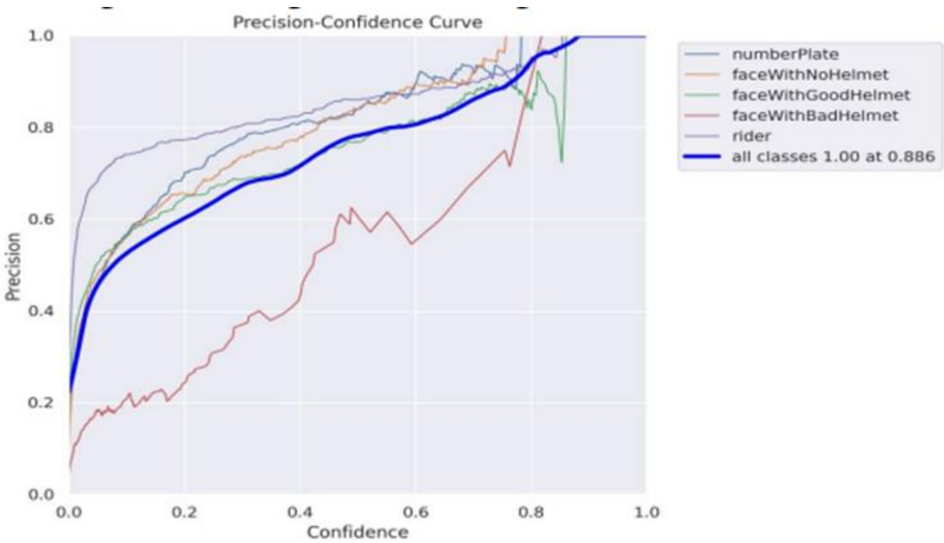

Fig. 5.2 Precision curve

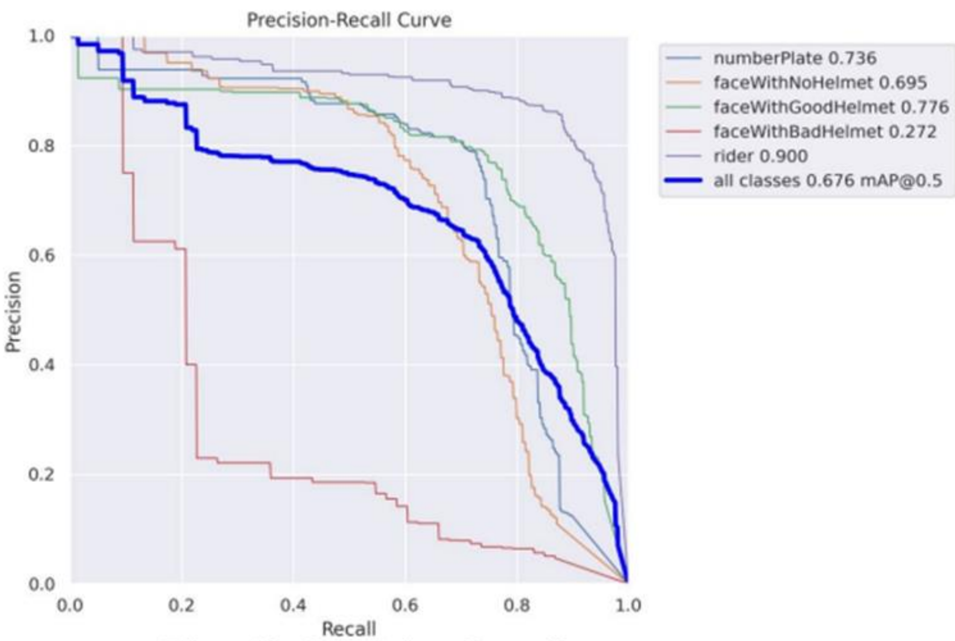

Fig. 5.3 Precision recall curve

Training mAP curve (orange) demonstrates a steady rise over training epochs, reflecting model's progressive learning. Similarly, the validation mAP curve (red) shows a positive trend, suggesting enhanced detection performance across all object categories in the dataset. Including numerical values on the y-axis would provide clearer insight into the exact mAP scores achieved.

YOLOv5 typically achieves mean Average Precision (mAP) scores of 0.82 and mAP50-95 of 0.67 with precision ranging from 80% to 90% and recall between 75% and 90% for detecting helmets and number plates. While it performs well overall, it can struggle with small objects or when items are partially obscured.

In contrast, YOLOv8, as an upgraded iteration, offers enhanced metrics with mAP value of 0.90 and mAP50-95 of 0.75, precision between 90% and 93%, and recall ranging from 80% to 95%. YOLOv8 is best in managing lower targets, occlusions, and more complicate surroundings.

When analogizing the two, YOLOv8 outperforms YOLOv5, specifically in detecting objects from difficult angles and under differing lighting conditions. Its raised speed and the accuracy form it conceptual for real life time uses like tracking of vehicles and safety performance.

Model	mAP @ 0.5	mAP @ 0.5:0.95
YOLOv5	0.82	0.67
YOLOv8	0.90	0.75

Fig. 5.4 result of Comparison experiment

Result-plot YOLOv5:

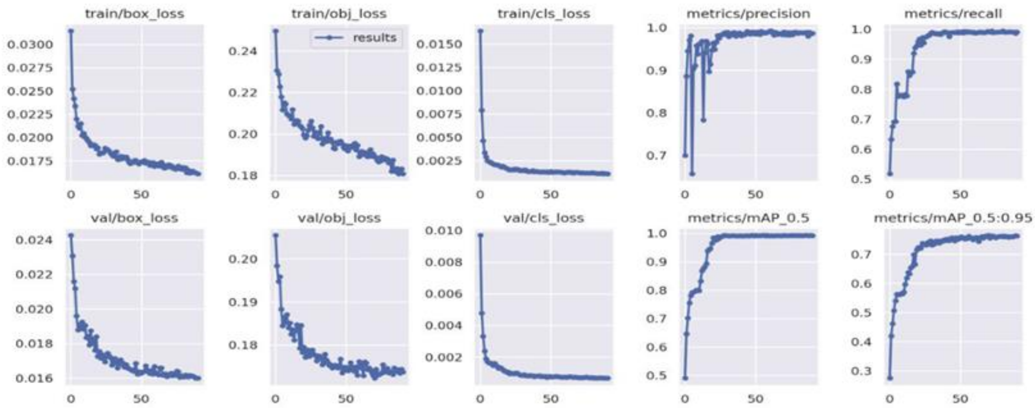

Fig. 5.5 the training and validation metrics of YOLOv5

Result-plot YOLOv8:

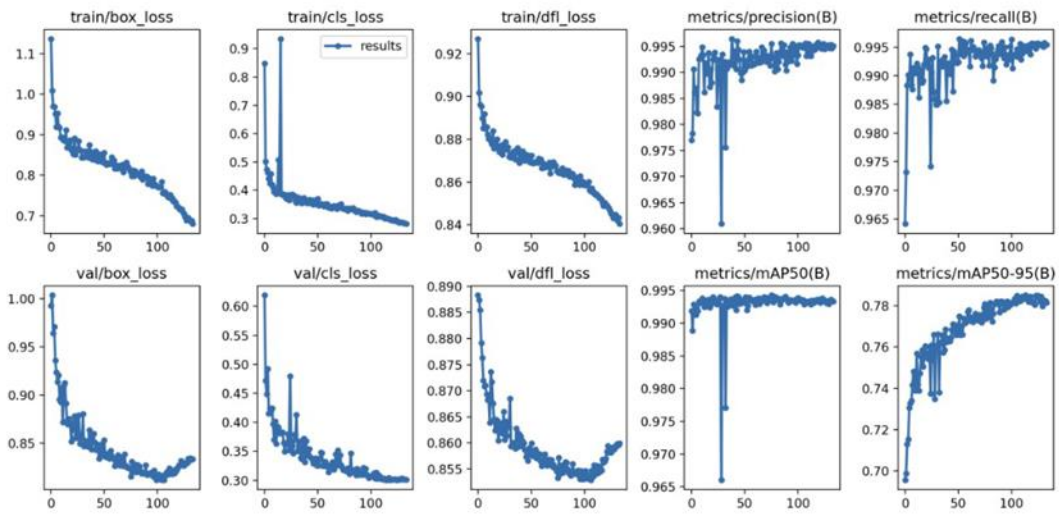

Fig. 5.6 the training and validation metrics of YOLOv8

Challenges: Both YOLOv5 and YOLOv8 face difficulties with occlusions, varying object angles, and environmental factors like poor lighting. still, YOLOv8 handles these issues more effectively thanks to its optimized framework.

Applications: These models are extensively used across different fields for helmet finding(to promote worker safety) and license plate recognition(for traffic management and toll systems).

Summary: While YOLOv5 remains a dependable option, YOLOv8 offers superior finding exactness, rapidly processing, and lesser robustness, forming it more acceptable for complex, real- time finding tasks.

5.1 LIMITATIONS

Both models struggle when helmets or number plates are partially blocked by objects, other vehicles, or riders. Detection accuracy drops significantly in such scenarios.Although YOLOv8 performs better than YOLOv5 in detecting small objects, identifying distant or small helmets and number plates remains a challenge, especially in low-resolution images. Poor lighting (e.g., night-time, glare) and adverse weather (rain, fog) can reduce the quality of image features, leading to missed or incorrect detections.

Detection performance can degrade when riders or number plates appear at unusual angles or orientations, as the models are more accustomed to standard frontal or side views.Accuracy is highly dependent on the training data. A small or unbalanced dataset (e.g., more images of good helmets than bad helmets) can bias the model and reduce generalizability.

While YOLOv5 and YOLOv8 are optimized for speed, real-time performance may still be limited on devices with lower computational power (e.g., edge devices or older GPUs). Models trained on specific geographical or cultural datasets (e.g., Indian roads) may not generalize well to different environments, such as Western countries or rural settings with different helmet styles or vehicle types.Incorrect or inconsistent labeling in the training dataset can lead to poor learning outcomes, affecting both detection and classification.

CHAPTER 6

CONCLUSIONS

In summary, both YOLOv5 and YOLOv8 are largely effective and effective real- time object discovery models, each offering distinct advantages depending on specific tasks conditions. YOLOv5 always be good choice due to its proven stability, ease of use, and supportive , forming it ideal for many practical operations. Alternatively, YOLOv8 builds upon YOLOv5's foundation with significant advancements in framework, performance, and inflexibility, making it more suited for further demanding scripts that bear lower delicacy and hastily conclusion. While YOLOv5 continues to be vastly espoused across colorful fields, YOLOv8 represents the coming generation of the YOLO series, furnishing enhanced capabilities for handling more complex and grueling discovery tasks.

vital advancements in YOLOv8 include advanced model effectiveness, upgraded point birth layers, and advancements to the backbone and neck networks, leading to hastily conclusion and better performance on different attack setups. also, YOLOv8 is more suited for training with limited data, making it ideal for scripts with lower annotated datasets. It also incorporates distended training options and evaluation criteria, allowing users to more effectively cover and upgrade the training process. The model excels in real- time object discovery across vids, images, and live webcam courses, handling complex situations with bettered precision and recall.

Despite the advancements introduced with YOLOv8, YOLOv5 remains broadly popular due to its well- established ecosystem, strong community support, and ease of use. numerous formulators continue to prefer YOLOv5 because of its proven responsibility and expansive proof across different operations, including security surveillance and independent driving. Both models prioritize speed and delicacy, but YOLOv8 offers bettered performance through architectural advancements and optimizations. For new systems taking advanced perfection and hastily conclusion, YOLOv8 may be the better option. still, for users familiar with YOLOv5 or those seeking a reliable result with abundant documentation and tutorials, YOLOv5 continues to be an best choice.

6.1 FUTURE SCOPE

Integration with Smart City Infrastructure: These models can be embedded into traffic monitoring systems for real-time enforcement of helmet laws and number plate recognition.Seamless integration with IoT devices and urban surveillance networks will enhance automated violation detection and improve public safety Optimized versions of YOLOv5 and YOLOv8 can be deployed on edge devices such as traffic cameras or embedded systems (e.g. Raspberry Pi). This allows instant, on-device decision-making without needing a high-performance server or constant cloud communication. Expanding and diversifying datasets—especially with different camera angles, lighting conditions, and helmet types—will further improve detection reliability. Continuous model fine-tuning using transfer learning and domain adaptation can yield better performance in regional or country-specific traffic scenarios. Future models can be designed to simultaneously detect multiple attributes (helmet color, number plate type, pillion riders, etc.). Integrating behavior analysis (e.g., identifying riders using phones while driving) could offer a broader safety monitoring framework. Integration with automated penalty systems using number plate recognition can streamline law enforcement and reduce human labor. Historical data from detection logs can help city planners and authorities understand traffic violations and optimize safety measures. As these systems become more prevalent, future work must consider privacy protection mechanisms such as anonymizing facial features or storing data securely. Ensuring compliance with local laws and ethical guidelines will be vital to gaining public trust and acceptance.

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