Thesis No.:

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SPEED ESTIMATION OF FRONT VEHICLE BASED ON MONOCULAR VISION SENSOR

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A thesis submitted in partial fulfillment of the requirements for the degree of

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Author

Abstract

This thesis addresses the critical task of measuring the speed of front vehicles using video analysis. The research methodology involves data collection from local roads, annotation of the collected dataset for vehicle detection using YOLOv5, and subsequent vehicle tracking utilizing the center track and bounding box ratio algorithms Following vehicle tracking, a novel approach for distance measurement is proposed, leveraging a custom model that utilizes the real-world height of vehicles and their corresponding image pixel ratios. This method provides nearly accurate estimations of the distances between vehicles and reference points in the environment. Furthermore, the study addresses the critical task of speed estimation by utilizing frame-per-second (fps) data in conjunction with the tracked vehicles. The resulting speed estimations are validated against ground truth measurements, establishing the reliability and effectiveness of the proposed methodology. The accuracy was around 93% in measuring distance and speed of vehicle. But for object detection in yolo model the accuracy was 81%. In conclusion, this thesis contributes to the domain of road safety and traffic management through a novel approach to speed measurement. By harnessing the power of video analysis, the study offers a solution to accurately compute the speeds of front vehicles on local road

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CHAPTER I

Introduction

1.1 Introduction

In the domain of road safety and transportation, the precise assessment of vehicle speeds, especially during overtaking maneuvers, is paramount for averting accidents and bolstering overall road safety standards [10]. Overtaking scenarios occurring on two-lane roads pose a significant challenge, demanding meticulous evaluation of the overtaking vehicle's speed in relation to oncoming traffic. Despite the critical importance of such assessments, traditional methods often fall short in accurately capturing the dynamic nature of overtaking maneuvers and the varying speeds involved. This research embarks on a quest to confront this challenge head-on by harnessing the power of advanced computer vision techniques and real-time video analysis to craft a robust and reliable speed measurement system.

In these overtaking scenarios, where vehicles must swiftly navigate past slower-moving counterparts while contending with oncoming traffic, the margin for error is exceedingly slim. A precise understanding of vehicle speeds is essential not only for the overtaking driver but also for ensuring the safety of all road users involved. Traditional speed measurement methods, reliant on fixed-point radar or manual observations, are often inadequate in capturing the nuanced dynamics of overtaking maneuvers, particularly on two-lane roads where real-time situational awareness is critical.

1.2 Problem statement

The lack of reliable and real-time speed measurement methods for overtaking vehicles during interactions with oncoming traffic on two-lane roads constitutes a critical challenge in road safety and transportation management [18]. Existing speed measurement approaches, rooted in traditional methodologies, often suffer from inherent delays and inaccuracies, thereby jeopardizing the safety of overtaking maneuvers and increasing the risk of collisions [19].

The consequences of unreliable speed measurements extend beyond individual overtaking decisions, permeating broader road safety and management initiatives. Without timely and accurate speed assessments, transportation authorities are hindered in their ability to proactively address safety concerns and optimize traffic flow on two-lane roads. Moreover, the absence of precise speed data impedes the implementation of effective road safety measures, leading to potentially hazardous driving conditions for all road users.

Furthermore, the burgeoning adoption of autonomous driving systems exacerbates the urgency of this issue. As both human-driven vehicles and autonomous vehicles coexist on roadways, the need for an adaptable speed measurement solution becomes increasingly pronounced. Autonomous driving systems rely heavily on accurate speed data to make informed decisions and navigate complex traffic scenarios safely[7]. Without a robust speed measurement system capable of providing real-time insights into overtaking maneuvers, the potential for accidents involving autonomous vehicles escalates, undermining public trust in autonomous driving technology and impeding its widespread adoption.

Therefore, the development of a reliable and real-time speed measurement system tailored specifically for overtaking scenarios on two-lane roads is imperative. Such a system would not only enhance the safety of overtaking maneuvers and mitigate collision risks but also facilitate more effective road safety and traffic management strategies. Additionally, the integration of this system into autonomous driving platforms would be pivotal in advancing the capabilities and safety standards of autonomous vehicles, paving the way for a safer and more efficient transportation landscape.

1.3 Objectives

1.3.1 Diverse Dataset Acquisition

This research aims to develop a comprehensive system for real-time speed measurement during overtaking maneuvers on two-lane roads, addressing critical challenges in road safety and transportation management. The objectives encompass various stages of system development and validation, including data collection, algorithm implementation, integration, and practical deployment considerations.

1.3.2 YOLOv5 Object Detection Model

The initial phase involves collecting a diverse dataset of video footage capturing overtaking scenarios under various environmental conditions. This dataset serves as the foundation for training a YOLOv5 object detection model, which will accurately identify vehicles in real-time video streams. Subsequent fine-tuning of the model focuses on optimizing detection performance for overtaking scenarios, ensuring robustness across different road and traffic conditions.

1.3.3 Distance Measurement and Vehicle Tracking

In parallel, algorithms for distance measurement and vehicle tracking are developed to complement the detection capabilities of the system. These algorithms utilize ground truth data such as vehicle height, camera focal length, and pixel-to-meter conversion factors to accurately compute distances between vehicles and reference points in the scene. Additionally, vehicle tracking algorithms leverage center position and bounding box ratio information to predict and maintain vehicle trajectories across consecutive frames, enabling the system to monitor overtaking maneuvers with precision[9].

1.3.4 Comprehensive System Evaluation

The culmination of these efforts lies in the integration of vehicle tracking and distance measurement modules with the YOLOv5 detection pipeline to enable comprehensive speed estimation during overtaking maneuvers. This integrated system undergoes extensive evaluation and validation to assess its accuracy, robustness, and real-time performance. Performance optimization techniques are explored to enhance computational efficiency and scalability, ensuring the system's viability for deployment in diverse real-world scenarios.

1.4 Scope and Required Tools

The project's scope revolves around the development of a real-time speed measurement system tailored specifically for overtaking maneuvers occurring on two-lane roads. This system aims to accurately measure vehicle speeds during such maneuvers, considering the unique challenges posed by dynamic traffic environments.

To achieve this objective, several essential tools and resources are required:

YOLOv5 Object Detection Model: This model will be utilized for real-time vehicle detection within video streams. By accurately identifying vehicles, the system can extract relevant data for speed measurement.

Python Programming Language: Python will serve as the primary language for algorithm development, data processing, and system integration. Its versatility and extensive libraries make it well-suited for handling various tasks throughout the project lifecycle.

Ground Truth Data: Ground truth data, including vehicle height, camera focal length, and pixel-to-meter conversion factors, are essential for accurate distance and speed calculations. These parameters provide reference points for calibrating the system and ensuring measurement accuracy.

Hardware Platform: A suitable hardware platform is necessary to support real-time processing of video streams. High-performance computing hardware ensures that the system can handle the computational demands of analyzing video data and calculating vehicle speeds without significant delays.

Validation Dataset: An annotated dataset is required for model training and system validation. This dataset contains labeled examples of vehicles in various scenarios, allowing the system to learn and improve its performance. Additionally, the validation dataset serves as a benchmark for evaluating the accuracy and reliability of the speed measurement system.

By leveraging these tools and resources, the project aims to develop a robust and reliable speed measurement system capable of accurately assessing vehicle speeds during overtaking maneuvers on two-lane roads in real-time.

1.5 Uniqueness of the thesis

The thesis stands out through its localized focus on vehicle speed measurement in Bangladeshi local road settings, addressing region-specific challenges for road safety enhancement. Uniquely, it combines YOLO model-based vehicle detection with real-time speed measurement, providing a comprehensive solution within a single system. The incorporation of two-lane road dynamics ensures a deeper understanding of traffic interactions. The thesis also embraces ethical considerations, acknowledging algorithmic bias and privacy concerns. Through extensive real-world testing and simulation-based validation, it demonstrates practical viability, promising a distinctive contribution to accurate speed measurement and road safety in complex traffic scenarios.

1.5.1 Localized Traffic Context

The research centers on the Bangladeshi local traffic environment, considering unique driving behaviors, road conditions, and traffic patterns specific to the region. This context-driven analysis sets the study apart from more generalized approaches.

1.5.2 Dual Perspective Speed Measurement

The thesis introduces a pioneering concept of simultaneously measuring the speeds of both oncoming and outgoing vehicles from the standpoint of a single vehicle. This innovative approach necessitates advanced tracking and analysis techniques to account for vehicles moving in opposing directions.

1.5.3 Local Data Authenticity

The research collects real-world data from Bangladeshi local roads, ensuring authenticity and relevance. The data acquisition process captures the nuanced dynamics of local traffic, including vehicle types, road conditions, and driving habits, enhancing the research's distinctiveness.

Figure 1.1: Showing both incoming and outgoing vehicles on a two-lane road.

1.5.4 Two-Lane Road Complexity

Operating within the constraints of a two-lane road setting adds complexity to the speed measurement process.

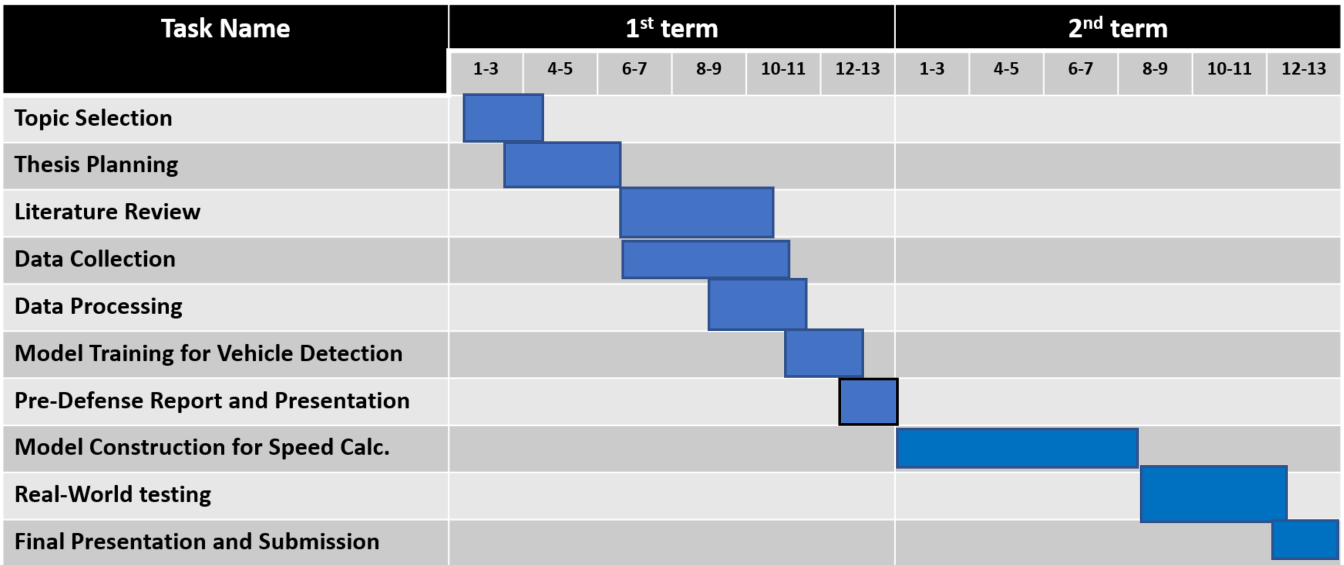
1.6 Project Planning

The project planning encompasses a meticulous framework for systematic execution. It delineates phases, tasks, and timelines, ensuring efficient progress. From topic selection and literature review to data collection, YOLO model training, and real-world testing, each phase has defined objectives. Workshops and conferences enhance skill acquisition, while comprehensive reporting maintains transparency. Funding sources are diversified, encompassing personal, university, and external grants. The project plan optimizes resources, accounting for unforeseen challenges. Through methodical implementation, the plan aims to yield valuable insights, innovative solutions, and impactful contributions to the field of vehicle speed measurement using computer vision

1.6.1 Project Timeline

The research for the thesis is divided into two phases, each contributing to our main goal. The first phase takes place during the first semester, and the second phase is scheduled for completion in the second semester. The target was to have the entire thesis completed by January 2024.

Table 1.1: Gantt Charts showing the work completed, proceeding and future planned



1.6.2 Concept of project

The accurate speed measurement system developed in this project carries significant societal implications, particularly in the realm of road safety. By providing precise speed data during overtaking maneuvers on two-lane roads, the system has the potential to significantly reduce the occurrence of accidents, ultimately benefiting society as a whole. Fewer accidents translate to fewer injuries and fatalities, leading to improved public health outcomes and a decrease in the burden on healthcare resources. Moreover, the societal impact extends beyond immediate safety benefits, as enhanced road safety fosters a sense of security and confidence among road users, contributing to overall community well-being.

Health Implications:

The project's focus on enhancing road safety through accurate speed measurement directly correlates with positive health outcomes. By minimizing the occurrence of accidents, the system helps alleviate the strain on healthcare resources by reducing the number of injuries and casualties resulting from road traffic incidents. Fewer road traffic injuries translate to fewer hospitalizations, surgeries, and rehabilitation efforts, thereby freeing up medical resources to address other healthcare needs. Additionally, the psychological toll of road accidents on survivors and their families is mitigated, leading to improved mental well-being within the community.

Safety Enhancement:

The real-time speed data provided by the project's system serves as a powerful tool for promoting safer driving behavior among road users. Armed with accurate information about their vehicle's speed relative to surrounding traffic, drivers are empowered to make more informed decisions, thereby minimizing the risk of collisions and accidents. Moreover, the availability of real-time speed feedback encourages adherence to speed limits and safe driving practices, fostering a culture of responsible driving behavior within the community. Ultimately, these safety enhancements contribute to the overall improvement of road safety and the reduction of traffic-related incidents.

Legal and Regulatory Considerations:

As with any technology with implications for public safety, adherence to local traffic laws and regulatory frameworks is paramount. Ensuring compliance with established legal standards and regulations is essential to the successful implementation and deployment of the project's speed measurement system. By adhering to legal requirements, the project not only mitigates the risk of legal liabilities but also reinforces its commitment to promoting responsible and law-abiding behavior among road users. Collaboration with relevant authorities and stakeholders facilitates the alignment of the project with existing legal and regulatory frameworks, thereby ensuring its effectiveness and legitimacy within the broader societal context.

Cultural Sensitivity:

In addition to legal considerations, cultural sensitivity plays a crucial role in the successful adoption and integration of the project's technology within the community. Adapting the system to local driving norms, customs, and cultural preferences is essential for fostering acceptance and trust among potential users. By incorporating cultural sensitivities into the design and implementation process, the project demonstrates respect for diverse cultural perspectives and enhances the likelihood of widespread adoption and utilization. Moreover, community engagement initiatives, such as public awareness campaigns and stakeholder consultations, facilitate meaningful dialogue and collaboration, further reinforcing the project's cultural sensitivity and societal relevance.

1.7 Application of the Works

The work's applications span road safety with accurate speed measurement, autonomous driving, urban planning for traffic optimization, law enforcement, and integration with smart transportation systems, contributing to safer roads and efficient mobility.

1.7.1 Road Safety Enhancement

The proposed speed measurement system aims to enhance road safety by providing accurate speed information to drivers during overtaking maneuvers, enabling them to make informed decisions and avoid potential collisions.

1.7.2 Autonomous Driving

The system's accurate speed assessment is invaluable for autonomous vehicles, ensuring safe interactions with other vehicles during overtaking scenarios and contributing to intelligent decision-making.

1.7.3 Traffic Management

The real-time speed measurement system can be integrated into traffic management frameworks to provide insights into traffic flow patterns and enhance overall road network efficiency.

1.8 Organization of the Thesis

The purpose of this section is to provide readers with a clear understanding of the order in which information is presented and to assist them in navigating the document. The remaining part of this thesis consists of the parts as follows:

Chapter 1: Introduction

This chapter provides an overview of the research background, motivation, and objectives. It introduces the problem statement, outlines the scope of the study, and identifies the required tools. Additionally, it offers a brief overview of the thesis structure.

Chapter 2: Literature Review

This chapter reviews existing literature related to speed measurement systems, real-time traffic analysis, legal and regulatory considerations, and cultural sensitivity in technology adoption. It provides context for the research and highlights gaps and opportunities for innovation.

Chapter 3: Methodology

This chapter details the methodology employed in the research, including data collection, preprocessing, and the implementation of the YOLOv5 object detection model. It describes the development of distance measurement and vehicle tracking algorithms and outlines the integration of speed measurement components.

Chapter 4: Implementation, Results, and Discussion

This combined chapter presents the system implementation details, including hardware and software setup, algorithm implementation, and integration with real-time video streams. It discusses the results obtained from system evaluation and analysis, addressing societal, health, safety, environmental, ethical, legal, and cultural considerations.

Chapter 5: Societal, Health, Environmental, Safety, Ethical, Legal, and Cultural Issues

This chapter delves into the broader societal implications of the research findings, including its impact on road safety, public health, environmental sustainability, and ethical considerations. It discusses legal and regulatory compliance, as well as cultural sensitivity in technology adoption.

Chapter 6: Addressing Complex Engineering Problems and Activities

This chapter focuses on the engineering challenges encountered during the research process, including technical complexities, algorithm optimization, and system scalability. It discusses the activities undertaken to address these challenges and proposes potential solutions.

Chapter 7: Conclusion

This chapter provides a summary of the key findings and contributions of the research. It offers recommendations for future research directions and concludes with closing remarks on the significance of the study in advancing the field.

References

This section lists all the references cited throughout the thesis, providing readers with access to the relevant literature and sources.

1.9 Conclusion

In conclusion, this introduction chapter has provided a comprehensive overview of the research context, motivations, and objectives. By delineating the problem statement and outlining the scope of the study, the groundwork has been laid for addressing the challenges associated with real-time speed measurement during overtaking maneuvers on two-lane roads. The identified objectives and required tools set the stage for the subsequent chapters, which will delve into the methodology, implementation, results, and discussion of the research findings. Through this study, we aim to develop a robust speed measurement system that not only enhances road safety but also addresses broader societal, health, environmental, ethical, legal, and cultural considerations. By the end of this thesis, we anticipate contributing valuable insights and solutions to the field of transportation engineering and traffic management.

CHAPTER II

Literature Review

2.1 Introduction

This literature review focuses on the pivotal area of **Vehicle Detection** and **Speed Measurement** within the domain of computer vision. It delves into the methodologies and advancements employed to accurately detect and track vehicles on roadways while simultaneously measuring their speeds. By investigating existing research in this realm, the review aims to illuminate the various techniques used for vehicle detection, tracking, and subsequent speed measurement. This analysis provides insights into the evolution of technology that underpins road safety and transportation efficiency.

2.2 Related works

2.2.1 Radar-Based Systems:

Doppler Radar: Kellner and Fink (2005) evaluated a dual radar system for traffic speed measurement based on Doppler shifts [1]. Doppler radar detects speed by analyzing the frequency change of reflected radar waves.

2.2.2 Laser-Based Systems:

LIDAR Technology: Guo and Feng (2017) proposed a LIDAR-based vehicle speed measurement system using time-of-flight principles [2]. Laser pulses measure the time taken to reflect off vehicles, enabling precise speed calculation.

2.2.3 Computer Vision-Based Systems:

Proposed Methodology: [3] This paper proposes a method for estimating the speed of a front vehicle using video data captured by a camera situated on vehicle. The proposed algorithm works by detecting and tracking the rear end of the front vehicle in consecutive video frames, and then calculating its speed based on the displacement of the rear end between frames. The authors present their algorithm which involves following steps:

Figure 2.1: Adjacent shadow line merging of vehicle   Figure 2.2: The location of suspected vehicle [3]

Step-1: Vehicle detection: First step is to detect the front vehicle from video frame. Authors used machine learning based object detection algorithm for this. They use the logic that under every vehicle there is a shadow and comparing the light of the road and under vehicle they detect the front vehicle.

Step-2: Rear end detection: Once the front vehicle is detected, the algorithm locates the rear end of the vehicle using a combination of edge detection and color segmentation.

Step-3: Tracking: Then they used a Kalman filter-based tracking algorithm to tracks the rear end of the vehicle, and estimates their speeds based on the displacement between frames and the time interval between frames.

Step-4: Data analysis: Finally, they create a system the that stores the data of speed measurement and other information in database which can be used for future analysis.

The authors evaluate the performance of their model using dataset of an urban roadways. They compare their result to those other speed measurement method and demonstrate that their system achieves higher accuracy. This system can be used for traffic management and automated driving system.

Remarks: I found that this paper tell us a unique system to detect vehicle that is using the shadow of vehicle. But I think it could result wrong for many times such as if a shadow of tree lies on the road then it will detect it as a vehicle. Another thing is the authors tell us the technique which measure only same directed vehicle speed but for both directed road it cannot perform perfectly or cannot measure the speed of opposite directed vehicle. .

Proposed methodology:

[4] In this paper authors proposed a method for measuring speed of vehicle using video which is captured by cameras installed along the roadways.

The proposed system consists a couple of cameras which installed alongside of roadways that capture the video footage of passing vehicles. The video then processed using computer vision techniques to extract the position and the speed of each vehicle. The system uses a Kalman filter to estimate the position and the velocity of every vehicle.

The system first detects the vehicle on the road then it detects the number plate of each vehicle. Then it detects the letter on the number plate and organize them.

Remarks: In this paper the proposed method uses cameras which are fixed at one position. If the camera is in movement then it cannot detect the speed of vehicle. Furthermore, we cannot measure the speed of vehicle using vehicles camera. Another problem is this method used the license plate of vehicle which means it cannot measure the speed of opposite directed vehicle.

Proposed methodology:

[5] They go over several methodologies, such as machine learning-based approaches, optical flow methods, and feature-based approaches.

The authors convert the region of interest into a non-linear form after first detecting it. Next, the background model is upgraded. They plot a line in the distance and follow each car that crosses it. The vehicle's velocity is then determined by measuring the time difference between two or more line crossings using the position tracking of one line to pass another.

Remarks: In this study, the authors offered a few approaches that can measure the velocity of a vehicle that crosses the camera's front line, but they are unable to determine the velocity of a vehicle that is pointed in the opposite direction. Here, on the side of the road, is where

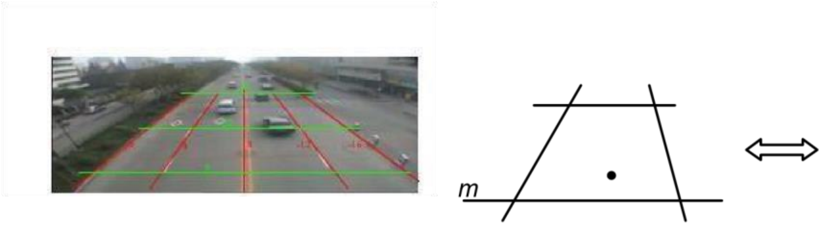


Figure 2.3: Shows the grid line which use to track vehicle [4]

the camera is fixed. Therefore, using this model, we are unable to determine the velocity from the vehicle's camera.

2.3 Comparison of Methods

Table 2.1: A comparison of these three methods for detecting and calculating vehicle speed

Aspect	**Radar-Based Systems**	**Laser-Based Systems**	**Computer Vision-Based Approaches**
Principle	Doppler Shift	Time-of-Flight	Optical Flow Analysis, Object Detection
Accuracy	Moderate	High	Variable, Depends on Algorithm
Cost	Moderate-High	High	Moderate-Low
Environmental Sensitivity	Sensitive to Weather Conditions	Limited Impact	Minimal Sensitivity

Real-Time Analysis	Yes	Yes	Yes
Integration Flexibility	Limited	Limited	Flexible
Application Scope	Generalized	Generalized	Versatile (Road Safety, ADAS, AVs)

2.4 Conclusion

In conclusion, the review of related works has shed light on various methodologies for measuring speed, and distance, and detecting vehicles in traffic scenarios. Existing approaches range from traditional radar systems to advanced computervision algorithms. The importance of accurate speed measurement for road safety and traffic management was emphasized, along with the need to consider broadersocietal, health, environmental, safety, ethical, legal, and cultural factors.While existing research provides valuable insights, gaps and opportunities forinnovation persist. This study aims to develop a comprehensive speed measurement system tailored for overtaking maneuvers on two-lane roads. By incorporating state-of-the-art technologies and methodologies, this research endeavors toaddress these challenges and contribute novel insights to transportation engineering and traffic management.

CHAPTER III

Methodology

3.1 Introduction

Efficient and accurate vehicle speed measurement is vital for road safety and transportation management. This research introduces a comprehensive methodology that combines image extraction, object tracking, and time-based calculations to determine vehicle speeds. By leveraging computer vision techniques, this approach aims to provide a robust and adaptable solution for real-time speed measurement on local roads. The methodology chapter delineates the systematic procedures followed to accomplish the objectives of the research. It encompasses various components, including data collection and processing, vehicle detection, tracking, distance measurement, and speed estimation. Each section elucidates the steps undertaken, methodologies employed, and the rationale behind them.

3.2 Proposed Methodology

The methodology is divided into four main parts:

3.2.1 Data Collection and Processing

Video data capturing overtaking maneuvers on two-lane roads was collected from road environments. Utilizing the OpenCV library, individual frames were extracted from the video footage. These frames were meticulously annotated to label vehicles and pertinent features essential for training the YOLOv5 object detection model. The annotation process involved marking bounding boxes around vehicles to provide ground truth data for model training.

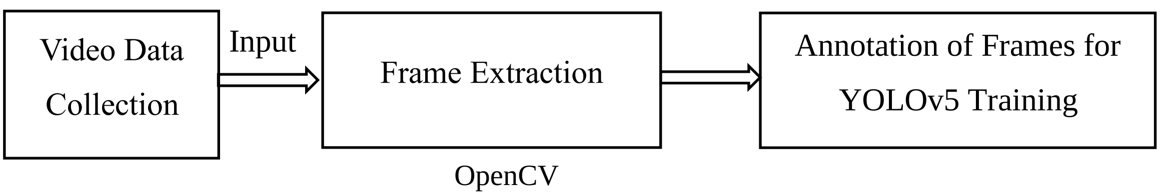


Figure 3.1: Showing flowchart of data collection and preprocessing

Frame extraction Algorithm:

Step-1: Take video data as input

Step-2: While Video ended go to step-4

Step-3: Save frame to a memory directory

Step-4: End

3.2.2 Vehicle Detection:

The pre-existing YOLOv5 model was trained using the custom dataset obtained from the previous step. Fine-tuning of the model optimized detection performance for overtaking scenarios. The output provided bounding box information and labels for each detected vehicle in the video frames. This facilitated the identification of vehicles in real-time video streams, forming the basis for subsequent tracking and speed measurement.

The YOLO v5 training process commences by extracting frames from video data depicting local road scenarios. These frames are then annotated to label vehicles, providing ground truth information. Subsequently, the annotated data is used for training the YOLO v5 model, enabling it to recognize vehicles within the frames. This training phase involves iterative optimization, refining the model's ability to detect vehicles accurately. The trained model is

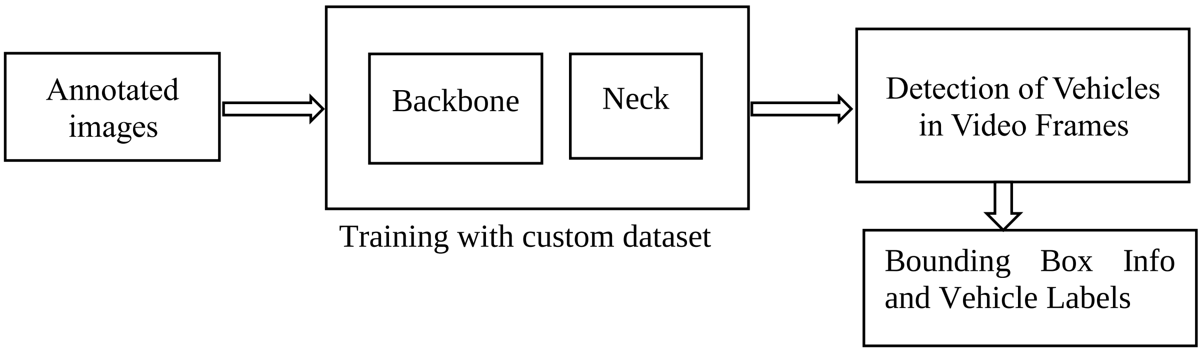


Figure 3.2: Showing training and detection process of yolov5 model

then validated against separate video data, assessing its proficiency in real-world scenarios. This holistic process amalgamates video data extraction, meticulous annotation, and iterative training to empower the YOLO v5 model for precise vehicle detection in local road environments.

Algorithm for vehicle detection:

Step-1: Take video data as input

Step-2: Load customize model directory

Step-3: while video end, go to step-8

Step-4: Extract frame and resize it as desired height

Step-5: Results = Model(frame)

Step-6: From Results extract Bounding Box info and label

Step-7: Draw bounding box and label, show

Step-8: End

3.2.3 Distance Measurement:

Distance measurement involved developing a custom model based on the lens and light equation [20]. This model utilized the ratio of the real vehicle height to the height of the vehicle in pixels, where the original height was provided as ground truth data, along with the focal length information of the camera. By computing the distance difference between vehicles in consecutive frames, accurate distance measurements were obtained, forming the basis for precise speed estimation.

Fig 3.3: Some picture taken from known distance to measure the ratio

Algorithm for distance measurement:

Step-1: Input real height of object and focal length data, and pixel to meter conversion ratio as ground truth

Step-2: Input Label and bounding box info from tracker class's output

Step-3: Return distance

Focal length info or pixel to meter conversion ratio can be found by taking some picture of vehicle from known distance and then find focal length from that.

Algorithm for focal length measurement:

Step-1: Input known distance and height of frame

*Step-2: (Distance * height in frame)/(real object height + height in frame)*

Step-3: Return focal length

3.2.4 Tracking and Speed Measurement:

Tracking was facilitated by utilizing the bounding box information and labels of vehicles in each frame [21]. Unique identifiers were assigned to vehicles based on center distance and bounding box information. If the center distance was less than 35 pixels and the bounding box ratio was less than 0.6, vehicles were assigned the same ID in different frames; otherwise, a new ID was assigned. Speed was calculated by dividing the distance difference

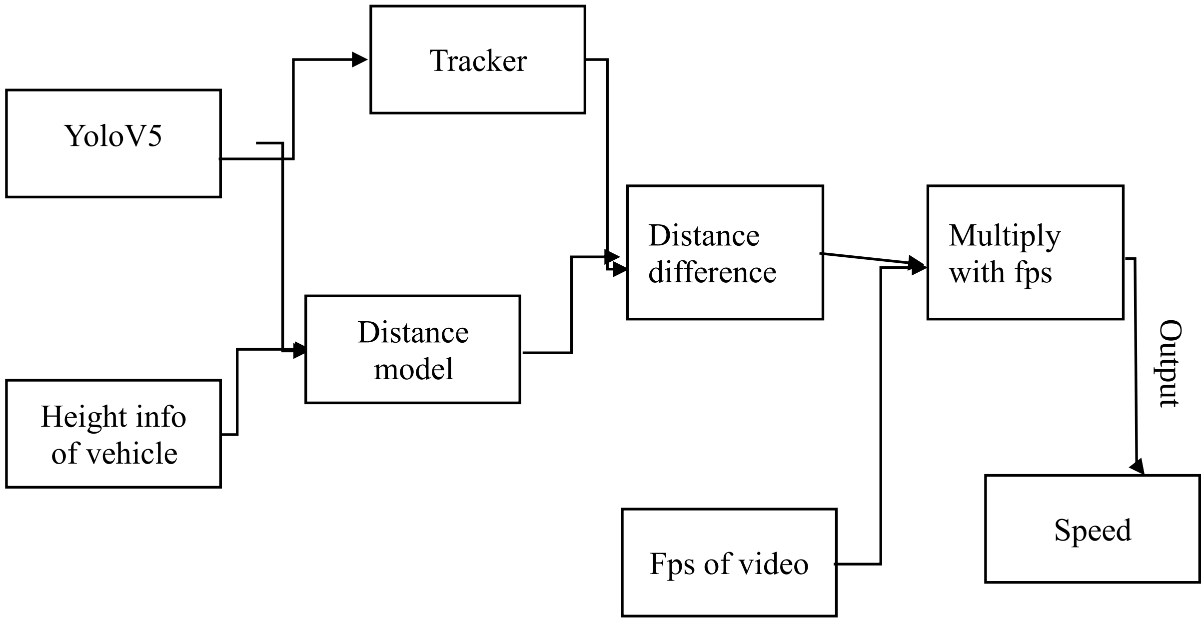


Figure 3.4: Object tracking and measuring the speed of every vehicle.

between vehicles in consecutive frames by the time difference obtained from the FPS information. Speed calculation entails post-detection analysis of tracked vehicle trajectories. The time difference between consecutive frames, combined with distance measurements of vehicles' movements, is harnessed to derive accurate speed values. This methodology ensures dynamic speed assessment, reflecting the real-time variations of vehicles on local roads. By integrating temporal and spatial data, the speed calculation process offers a comprehensive understanding of vehicle velocities, contributing to enhanced road safety and efficient traffic management.

Algorithm for tracker:

Step-1: Input bounding box and label from detection model's output

Step-2: If Bbox ratio > 0.6 and center point distance < 35:

Assign same id. Else id = id + 1 assign id

Step-3: After first 10 frame: label[id] = most common id in first 10 frame

Step-4: Keep label same for a unique id

Step-5: return bounding box and label

Overall algorithm for speed estimation from test video:

Step-1: Take video data as input and fps(Frame per second)

Step-2: Load customize model directory

Step-3: while video end, go to step-11

Step-4: Extract frame and resize it as desired height

Step-5: Results = Model(frame)

Step-6: From Results extract Bounding Box info and label as detections dictionary

Step-7: Tracked object = tracker(detections)

Step-8: Find distance from tracked object and store it

Step-9: speed = (distance of frame (i) – distance of frame (j))(fps/(i-j))*

Step-10: Draw bounding box and speed and show

Step-11: End

For resizing image here bilinear interpolation has been used[17]. In bilinear interpolation it calculates it's surrounding pixel values and then interpolate for estimating the original value.

Algorithm for resizing image:

1.Calculate the scale factors for width and height:

2. Create an empty array for the resized image with dimensions

3. For each pixel in the resized image:

Calculate the corresponding coordinates in the original image using the scale factors.

Determine the four nearest pixels

Perform bilinear interpolation to calculate the pixel value

Assign the interpolated value to the corresponding pixel in the resized image.

4. Return resized image.

3.3 Conclusion

In conclusion, the methodology chapter outlines a comprehensive approach for developing a real-time speed measurement system tailored for overtaking maneuvers on two-lane roads. By systematically collecting, processing, and analyzing video data, the study lays the foundation for accurate speed estimation in dynamic traffic environments.

The data collection and processing phase involved extracting individual frames from video footage and annotating them to provide ground truth data for training the YOLOv5 object detection model. This meticulous annotation ensures the model's efficacy in detecting vehicles in real-time video streams, forming the cornerstone of the subsequent analysis.

The vehicle detection process, facilitated by the fine-tuned YOLOv5 model, enables the identification of vehicles and extraction of essential information, including bounding box coordinates and labels. This information serves as the basis for vehicle tracking and speed measurement, enabling the system to monitor vehicle movements and estimate speed accurately.

The tracking and speed measurement components employ advanced algorithms to assign unique identifiers to vehicles and calculate their speed based on distance differences between consecutive frames. Additionally, the distance measurement model, utilizing the lens and light equation, ensures precise distance calculations by incorporating the ratio of the real vehicle height to the height of the vehicle in pixels and the focal length information of the camera.

CHAPTER IV

Implementation and Results and Discussion

4.1 Introduction

This study delves into the implementation, results, and subsequent discussion of an initial phase focused on vehicle detection using the YOLO v5 model. By leveraging a self-collected dataset depicting local road scenarios, the study aims to lay the foundation for accurate vehicle detection, a critical element in the larger context of comprehensive speed measurement. While the project is in its nascent stage, the successful integration of the YOLO v5 model with the collected dataset signifies an essential milestone. This introductory overview sets the stage for evaluating the outcomes of the vehicle detection process and discussing the potential implications of these findings. As we progress, the study intends to extend beyond detection to encompass tracking, speed calculation, and a more comprehensive evaluation of the entire speed measurement system's performance in real-world conditions.

4.2 Experimental Setup

The optimal setup proposed by the authors:

Software Setup:

OpenCV: OpenCV will be used for video processing tasks, including frame extraction, image manipulation, and annotation.

YOLOv5: YOLOv5 will serve as the primary vehicle detection model. The pre-trained YOLOv5 model will be fine-tuned using the custom dataset obtained from the data collection phase.

Python: Version 3.7 or later -Python programming language will be utilized for algorithm development, data processing, and system integration. Various libraries such as NumPy, Pandas, and Matplotlib will be used for data manipulation, analysis, and visualization.

IDE (Integrated Development Environment): Any preferred IDE such as PyCharm, Jupyter Notebook, or Visual Studio Code will be used for coding and project management.

Annotation Tool: An annotation tool such as LabelImg or VOTT (Visual Object Tagging Tool) will be employed for annotating the video frames to provide ground truth data for training the YOLOv5 model.

Hardware Setup:

CPU (Central Processing Unit): Intel Core i7 or equivalent - A powerful CPU is necessary for efficient video processing and algorithm execution.

GPU (Graphics Processing Unit): NVIDIA GeForce RTX 30XX series or equivalent - A GPU with CUDA support is recommended for accelerated model training and inference tasks, particularly for fine-tuning the YOLOv5 model.

Memory (RAM): Minimum 16GB DDR4 RAM - Sufficient RAM is required for handling large datasets and model training tasks efficiently.

Storage: SSD (Solid State Drive) - SSD storage offers faster read/write speeds, facilitating quicker data access and manipulation.

Camera: High-resolution camera with adjustable focal length - A camera capable of capturing clear and detailed video footage is essential for accurate vehicle detection and distance measurement.

Operating System: Any preferred operating system such as Windows, macOS, or Linux - The chosen OS should be compatible with the required software tools and libraries.

Additional Peripherals: Monitor, keyboard, and mouse - Standard peripherals for system interaction and monitoring.

By configuring the software and hardware components as outlined above, the experimental setup will be capable of effectively implementing the proposed methodology for developing the real-time speed measurement system.

4.3 Evaluation Metrics

For the evaluation of our detection, tracking, distance measurement, and speed estimation correctly we need some evaluation matrix. These metrics include:

Detection Accuracy: This metric measures the accuracy of vehicle detection in the video frames. It evaluates the percentage of correctly identified vehicles compared to the total number of vehicles present in the frames.

Bounding Box Accuracy: Bounding box accuracy assesses the precision of the detected bounding boxes around vehicles. It calculates the Intersection over Union (IoU) score, indicating the overlap between the ground truth bounding boxes and the detected bounding boxes.

Distance Measurement Accuracy: Distance measurement accuracy quantifies the precision of distance calculations between vehicles in consecutive frames. It compares the computed distances with ground truth measurements obtained from physical measurements on the road.

Speed Estimation Accuracy: Speed estimation accuracy assesses the correctness of vehicle speed calculations based on distance differences between frames and time differentials obtained from frame rates. It compares the calculated speeds with actual vehicle speeds measured using speed sensors or radar guns.

Real-Time Performance: Real-time performance assesses the system's ability to process video streams in real-time. It measures the system's latency, i.e., the delay between capturing a frame and producing the output, ensuring that the system can handle video streams at the required frame rates without significant delays.

By considering these evaluation metrics collectively, a comprehensive understanding of the effectiveness of our speed estimation method has been achieved.

4.4 Dataset

4.4.1 Dataset for training yolov5

Approximately 40 two-minute videos were collected from various locations in the Khulna city area, including KUET Road, Fulbarigate, Mujgunni, and other key locations. The camera of an iPhone XS Max was utilized for video capture. To address shaking issues inherent in capturing footage while riding a motorbike, a stabilizing device was employed, effectively reducing shaking and ensuring smoother video quality. This setup enabled the recording of footage while in motion, providing dynamic and realistic representations of real-world traffic scenarios and pedestrian activities in urban environments.

4.4.2 Dataset for measuring distance

For distance measuring, accurate pixel to height ratio is needed and so needed the focal length of the camera. So, around 100 photos of different vehicle's at some certain distance (5 meter, 10 meter, 15 meter, 20 meter, 25 meter, 30 meter) has been collected and then using focal length measuring algorithm focal has been measured.

Fig 4.1: Zhiyun smooth 4 gamble

Figure 4.2: Shows some moments from collected Video data

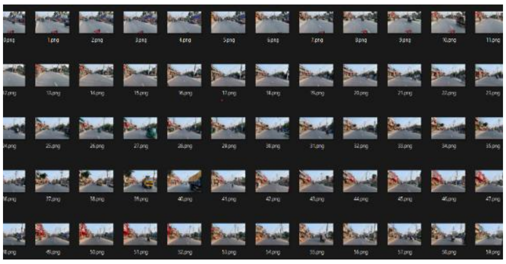
4.5 Implementation and Results

4.5.1 Data collection:

Data collection involved capturing video footage from local road environments, crucial for model training and evaluation. Customized video recording equipment was deployed to capture diverse traffic scenarios, considering factors such as vehicle density and road conditions. The collected dataset forms the bedrock for model development, enabling accurate vehicle detection. This meticulous data acquisition process ensures that the model is exposed to real-world complexities, facilitating robust performance across varying traffic situations. Video data has been collected from local Bangladeshi area like Fulbarigate, inside KUET, Muzgunni etc.

4.5.2 Data Pre-processing:

Extracting images from video data: Open CV library has been used for extracting images from video data



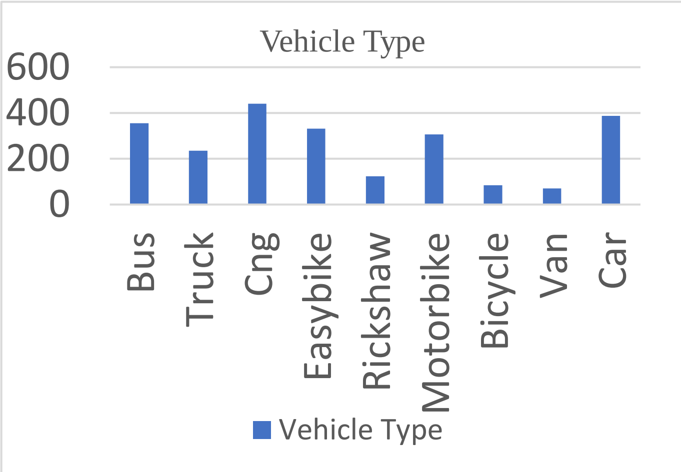


Figure 4.3: Extracted

images from video data size of the data

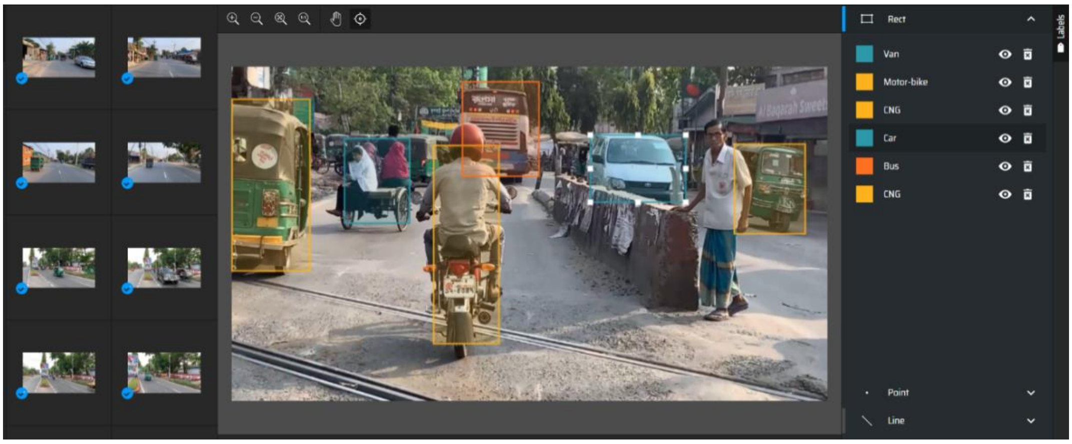
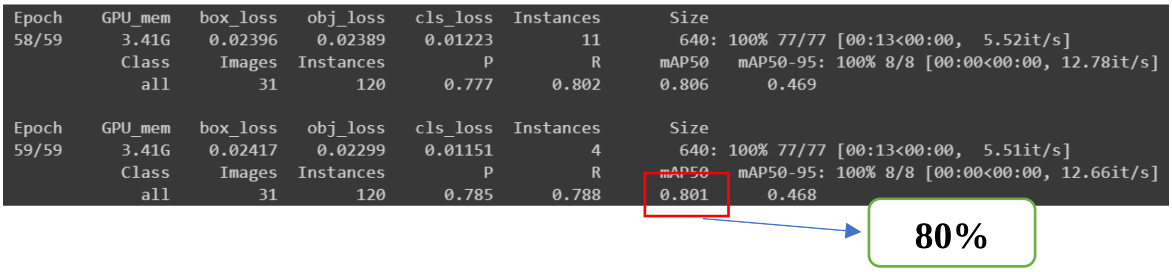


Figure 4.4: Shows the annotation of images

Annotate vehicle from extracting images: Makesense.ai has been used for annotating every vehicle inside the extracted images

4.5.3 YOLO v5 model training and testing:

The YOLO v5 model training encompassed utilizing the collected dataset for model enhancement. Annotated images provided ground truth labels, aiding the model in recognizing vehicles. The training process involved iterative optimization, where the model learned to accurately detect vehicles in varying local road scenarios. Parameters were fine-tuned to achieve higher detection precision. This training phase facilitated the YOLO v5



```
Epoch    GPU_mem   box_loss   obj_loss   cls_loss  Instances       Size
58/59      3.41G    0.02396    0.02389    0.01223         11        640: 100% 77/77 [00:13<00:00,  5.52it/s]
           Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 8/8 [00:00<00:00, 12.78it/s]
             all         31        120      0.777      0.802      0.806      0.469

Epoch    GPU_mem   box_loss   obj_loss   cls_loss  Instances       Size
59/59      3.41G    0.02417    0.02299    0.01151          4        640: 100% 77/77 [00:13<00:00,  5.51it/s]
           Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 8/8 [00:00<00:00, 12.66it/s]
             all         31        120      0.785      0.788      0.801      0.468
```


Figure 4.5: Show the result after training Yolo v5 model

Sometimes model wrongly detected a class and sometimes it misses the class.

Figure 4.6a: wrongly detected truck as car

Figure 4.6b misses the class Motor-bike from detections

model's evolution into a proficient vehicle detector, capable of identifying vehicles within the collected dataset's dynamic traffic environments.

Qualitative results:

After 60 epoch approximately to 80% accuracy has been found in yolov5 detection model.

Quantitative results:

This model was tested with another video that was not in the training set. Here shows some moment from that Video

Figure 4.7: Shows the detected vehicle inside the bounding box

4.5.4 Distance Measurement Model Development:

To accurately measure the distance of vehicles from the camera, we leveraged the principles of light refraction through lenses. Utilizing established optical equations, specifically the rules governing light refraction in lenses, we formulated a distance measurement model tailored for our system.

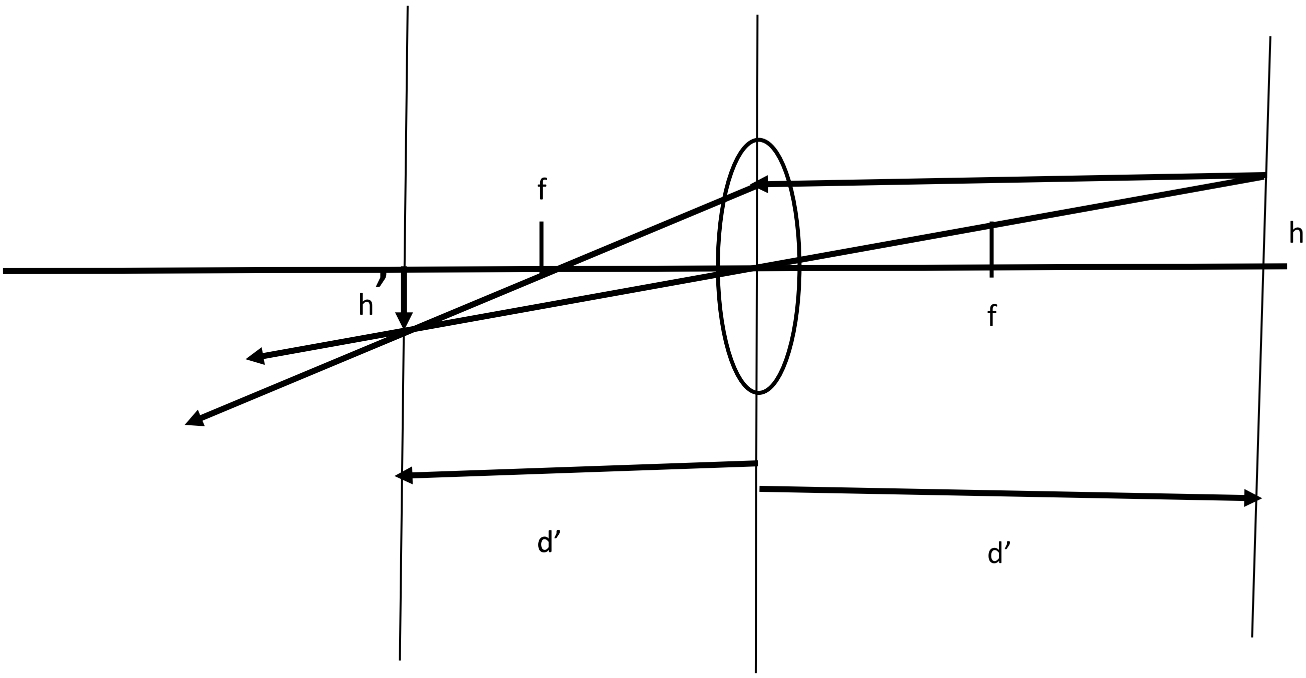


Figure 4.8: Shows how refraction of light works through camera’s lens

According to the lens equation:

$$\frac{1}{f} = \frac{1}{d'} + \frac{1}{d} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ldots (i)$$

where d represents the object distance, d' represents the image distance, and f represents the focal length of the camera. Additionally, the ratio of object height (h) to image height (h') is equal to the ratio of object distance (d) to image distance (d'), denoted as c :

$$\left|\frac{h}{h'}\right| = \frac{d}{d'} = c \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(ii)}$$

Combining equations (i) and (ii), we obtain:

$$\frac{d}{f} = \frac{d}{d'} + 1 = c + 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(iii)}$$

Solving for d in terms of f, we arrive at:

$$d = (c + 1) \times f \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(iv)}$$

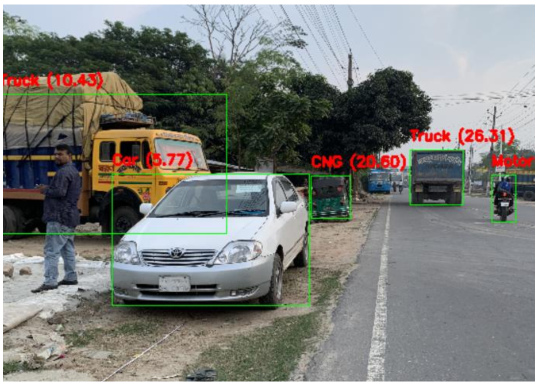
This formula, derived from the principles of light refraction, allows us to calculate the distance of a vehicle from the camera given the known focal length of the camera and the ground truth height of the object. By utilizing this model, we can accurately estimate the distances of vehicles in the captured images, laying the foundation for precise speed estimation in our system.

To accurately determine the focal length of the camera, we conducted a calibration process using images captured at known distances from the camera. By applying Equation (v), derived from the distance measurement model, we computed the focal length (f) based on the known real distance (d) and the ratio (c) of image height to object height.

According to Equation (v):

$$f = \frac{d}{1 + c} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(v)}$$

Figure 4.9: Sample photo capture in certain distance



Actual distance = 5m

Measured distance = 5.7m

Error = (5.7-5)/5 *100 %= 14%

Accuracy = 86%

Figure 4.10: Showing accuracy of distance measurement for a car

where d represents the real distance between the camera and the object, and c denotes the ratio of image height to object height.

By capturing images of vehicles placed at known distances, such as 5 meters, 10 meters, and 15 meters from the camera, we obtained a series of reference images for calibration. Using these images, along with the ground truth distances, we calculated the corresponding focal lengths.

Quantitative results:

For estimating speed of vehicle accurately we must need to calculate the distance of vehicle in every frame first. This customize model help to find the distance of a vehicle in a frame.

Accuracy calculation:

Actual distance = 10m

Measured distance = 10.71m

Error = (10.71-10)/10 *100 %

= 7.1%

Accuracy = 92.9%

Figure 4.11: Showing accuracy of distance measurement for a car

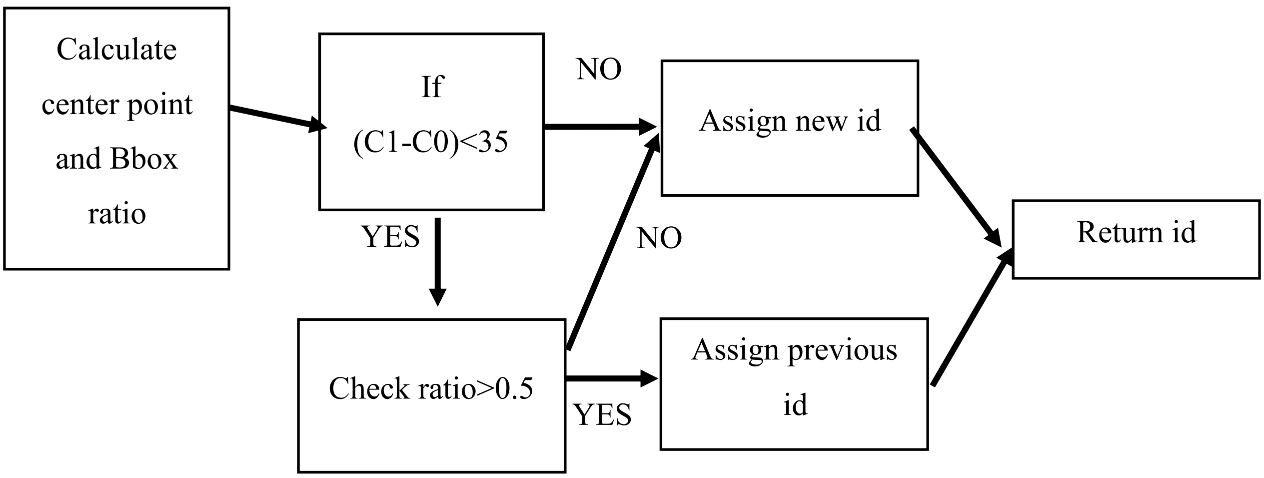


Figure 4.12: working principle of Tracker class

4.5.5 Tracking:

Our tracking algorithm is crucial for maintaining continuity and accuracy in identifying vehicles as they move through the video stream. Here's a detailed overview of our tracking

Our tracking algorithm begins by analyzing the initial frames of the video stream. For the first 10 frames, we calculate the center point distance and bounding box ratio between consecutive frames. These metrics allow us to assign a unique identifier (ID) to each vehicle based on its movement characteristics.

Once we have assigned IDs to the vehicles, we focus on assigning labels. To ensure consistency, we analyze the labels observed in the past 10 frames for each vehicle. The most frequently occurring label within this window is then assigned to the corresponding vehicle ID. This approach helps maintain stable labeling even in scenarios with temporary occlusions or changes in orientation. The Kalman filter is employed to predict the bounding box information of vehicles in subsequent frames, ensuring smooth and accurate tracking even in cases where the YOLO model misses detection. Specifically, when the YOLO model fails to detect a vehicle in certain frames, the bounding box information is estimated using the predictions generated by the Kalman filter. To enhance the accuracy of the tracker, a labeling mechanism is introduced based on the observations from the initial frames. By analyzing the first ten frames, a predominant label for the vehicle is determined, which serves as a reference for subsequent detections. This approach not only compensates for missed detections but also maintains the integrity of the tracking process, thus ensuring the reliability and robustness of the proposed vehicle tracker. Through this integration of Kalman filtering with YOLO detection and the incorporation of a labeling strategy, the tracker demonstrates effective adaptability to various tracking scenarios, as evidenced by experimental results and evaluations.

Qualitative results:

In most of the cases tracker find the vehicle in separate frame same id. But if our model give a wrong detection in a frame like motorbike detected as CNG middle of a frame then it'll give a wrong distance as our distance calculator model depends on the ground truth of vehicle's height.

Figure 4.13: Showing id remains unique in several frames

Fig 4.14: Failed to assign same id in different frame for same object

To ensure robust tracking, we maintain the assigned labels for each vehicle until it disappears from the screen. This label persistence prevents unnecessary fluctuations and ensures smooth tracking throughout the video stream.

As only center point distance was used for tracking the tracker often gives poor results. After using bounding box ratio, it resolved mostly.

Finally, the tracking algorithm outputs the ID, bounding box coordinates, and assigned label for each tracked vehicle. This information is then passed to the main function for further analysis and processing.

Through our tracking algorithm, we achieve reliable and consistent vehicle tracking in real-time video streams. By leveraging center point distance, bounding box ratios, and label analysis, we ensure accurate identification and persistence of vehicle IDs, enhancing the overall effectiveness of our speed measurement system.

4.5.6 Speed Measurement:

To calculate the speed of each tracked vehicle, we utilize the distance obtained from the distance measurement model and the IDs assigned by the tracker class [22].

Table 4.1: Showing framewise data of a sample test video and error and accuracy

Frame No.	Distance	Speed	Frame Height	Real Speed	Error (Absolute)	Accuracy (%)
0	40.71001	0	36	-40	40	0
1	39.61595	0	37	-40	40	0
2	39.61595	0	37	-40	40	0
3	40.71001	0	36	-40	40	0
4	39.61595	0	37	-40	40	0
5	39.61595	0	37	-40	40	0
6	39.61595	-23.6316	37	-40	16.36843	59.07893
7	38.57948	-23.6316	38	-40	16.36843	59.07893
8	39.61595	-23.6316	37	-40	16.36843	59.07893
9	39.61595	-23.6316	37	-40	16.36843	59.07893
10	37.59616	-23.6316	39	-40	16.36843	59.07893
11	36.662	-33.6295	40	-40	6.370457	84.07386
12	36.662	-33.6295	40	-40	6.370457	84.07386
13	35.77342	-33.6295	41	-40	6.370457	84.07386
14	34.92715	-33.6295	42	-40	6.370457	84.07386

15	34.12024	-33.6295	43	-40	6.370457	84.07386
16	32.614	-47.4463	45	-40	7.446332	81.38417
17	32.614	-47.4463	45	-40	7.446332	81.38417
18	34.12024	-47.4463	43	-40	7.446332	81.38417
19	34.12024	-47.4463	43	-40	7.446332	81.38417
20	33.35	-47.4463	44	-40	7.446332	81.38417
21	33.35	-39.744	44	-40	0.255995	99.36001
22	31.91	-39.744	46	-40	0.255995	99.36001
23	30.59	-39.744	48	-40	0.255995	99.36001
24	29.97041	-39.744	49	-40	0.255995	99.36001
25	30.59	-39.744	48	-40	0.255995	99.36001
26	30.59	-43.7184	48	-40	3.718406	90.70399
27	31.23596	-43.7184	47	-40	3.718406	90.70399
28	31.23596	-43.7184	47	-40	3.718406	90.70399
29	31.23596	-43.7184	47	-40	3.718406	90.70399
30	30.59	-43.7184	48	-40	3.718406	90.70399
31	30.59	-36.432	48	-40	3.567995	91.08001
32	29.97041	-36.432	49	-40	3.567995	91.08001
33	29.97041	-36.432	49	-40	3.567995	91.08001
34	29.3756	-36.432	50	-40	3.567995	91.08001
35	28.80412	-36.432	51	-40	3.567995	91.08001
36	27.72585	-38.5751	53	-40	1.424936	96.43766
37	28.25462	-38.5751	52	-40	1.424936	96.43766
38	28.25462	-38.5751	52	-40	1.424936	96.43766
39	28.25462	-38.5751	52	-40	1.424936	96.43766
40	27.21667	-38.5751	54	-40	1.424936	96.43766
41	27.21667	-36.432	54	-40	3.567995	91.08001
42	26.726	-36.432	55	-40	3.567995	91.08001
43	25.79632	-36.432	57	-40	3.567995	91.08001
44	24.518	-36.432	60	-40	3.567995	91.08001
45	24.518	-36.432	60	-40	3.567995	91.08001

46	24.518	-43.7184	60	-40	3.718406	90.70399
47	24.92966	-43.7184	59	-40	3.718406	90.70399
48	24.92966	-43.7184	59	-40	3.718406	90.70399
49	25.79632	-43.7184	57	-40	3.718406	90.70399
50	25.35552	-43.7184	58	-40	3.718406	90.70399
51	25.35552	-28.2662	58	-40	11.73379	70.66553
52	24.92966	-28.2662	59	-40	11.73379	70.66553
53	24.518	-28.2662	60	-40	11.73379	70.66553
54	23.73452	-28.2662	62	-40	11.73379	70.66553
55	23	-28.2662	64	-40	11.73379	70.66553
56	23	-32.7888	64	-40	7.211196	81.97201
57	22.31	-32.7888	66	-40	7.211196	81.97201
58	20.75507	-32.7888	71	-40	7.211196	81.97201
59	20.47	-32.7888	72	-40	7.211196	81.97201
60	20.19274	-32.7888	73	-40	7.211196	81.97201
61	20.19274	-37.4301	73	-40	2.569858	93.57535
62	20.19274	-37.4301	73	-40	2.569858	93.57535
63	20.47	-37.4301	72	-40	2.569858	93.57535
64	20.75507	-37.4301	71	-40	2.569858	93.57535
65	19.15572	-37.4301	77	-40	2.569858	93.57535
66	19.40474	-22.3998	76	-40	17.60025	55.99938
67	18.91308	-22.3998	78	-40	17.60025	55.99938
68	17.78759	-22.3998	83	-40	17.60025	55.99938
69	17.57857	-22.3998	84	-40	17.60025	55.99938

70	17.57857	-22.3998	84	-40	17.60025	55.99938
71	17.37447	-28.233	85	-40	11.76698	70.58255
72	16.79	-28.233	88	-40	11.76698	70.58255
73	16.24407	-28.233	91	-40	11.76698	70.58255
74	15.73298	-28.233	94	-40	11.76698	70.58255
75	15.25351	-28.233	97	-40	11.76698	70.58255
76	14.95	-35.5625	99	-40	4.437507	88.90623
77	14.24231	-35.5625	104	-40	4.437507	88.90623
78	13.59954	-35.5625	109	-40	4.437507	88.90623
79	13.59954	-35.5625	109	-40	4.437507	88.90623
80	13.24143	-35.5625	112	-40	4.437507	88.90623
81	12.68539	-37.5371	117	-40	2.462915	93.84271
82	12.17492	-37.5371	122	-40	2.462915	93.84271
83	11.70465	-37.5371	127	-40	2.462915	93.84271
84	11.35428	-37.5371	131	-40	2.462915	93.84271
85	11.18699	-37.5371	133	-40	2.462915	93.84271
86	11.02467	-38.9048	135	-40	1.095167	97.26208
87	11.10523	-38.9048	134	-40	1.095167	97.26208
88	10.63914	-38.9048	140	-40	1.095167	97.26208
89	10.56532	-38.9048	141	-40	1.095167	97.26208
90	10.56532	-38.9048	141	-40	1.095167	97.26208
91	9.692858	-34.6587	154	-40	5.341282	86.6468
92	9.692858	-34.6587	154	-40	5.341282	86.6468
93	9.28143	-34.6587	161	-40	5.341282	86.6468
94	9.008796	-34.6587	166	-40	5.341282	86.6468
95	8.702559	-34.6587	172	-40	5.341282	86.6468
96	8.463221	-40.2356	177	-40	0.235643	99.41089

97	8.281272	-40.2356	181	-40	0.235643	99.41089
98	7.98149	-40.2356	188	-40	0.235643	99.41089
99	7.553016	-40.2356	199	-40	0.235643	99.41089
100	7.37353	-40.2356	204	-40	0.235643	99.41089
101	6.914771	-34.4713	218	-40	5.528666	86.17833
102	6.457693	-34.4713	234	-40	5.528666	86.17833
103	6.62158	-34.4713	228	-40	5.528666	86.17833
104	6.404916	-34.4713	236	-40	5.528666	86.17833
105	5.647398	-34.4713	269	-40	5.528666	86.17833
106	5.944824	-35.409	255	-40	4.590962	88.5226

From Table 4.1 when the distance is more than 30 meter, the error increase and the accuracy has been found low. But inside the 30 meter range accuracy got high.

Distance Measurement Model Output: The distance measurement model provides us with accurate distance measurements for each tracked vehicle in consecutive frames.

Tracker Class ID: The tracker class assigns a unique identifier (ID) to each tracked vehicle, allowing us to associate the distance measurements with specific vehicles.

Speed Calculation: Once we have the distance between consecutive frames for each tracked vehicle, we multiply this distance by the frames per second (FPS) obtained from ground truth data. This calculation yields the speed of the vehicle in meters per second (m/s).

Output: The calculated speed for each vehicle is then recorded and made available for further analysis and processing.

By combining the distance measurements from the distance measurement model with the IDs provided by the tracker class and incorporating the FPS information, we accurately calculate the speed of each tracked vehicle in the video stream. This speed estimation process forms a crucial component of our speed measurement system, providing valuable insights into vehicle movements and facilitating effective traffic management and safety measures.

Quantitative results:

The model has been tested on a Motorbike which speed was consistently 30km/h and the model gives results which accuracy was around 90-95%.

Actual speed = 30 km/h

Measured = 28.85 [- means incoming]

Accuracy = (100 - (30 – 28.85)/30 * 100)%

= 95%

al speed = 30 km/h

Measured = 24.23 [- means incoming]

Accuracy = (100 - (30 – 24.23)/30 * 100)%

= 81%

Actual speed = 30 km/h

Measured = 31.38 [- means incoming]

Accuracy = (100 - (30 – 31.38)/30 * 100)%

= 95.4%

4.5.7 Analysis of the results

The analysis of the results obtained from each phase of the system, as discussed in the thesis, provides crucial insights into its performance:

Detection Phase:

With an accuracy of 80.1%, the detection phase demonstrates the system's capability to identify vehicles accurately within the video stream. While this accuracy level indicates effective detection, further optimization could potentially enhance detection performance in complex scenarios or under challenging lighting conditions.

Distance Measurement Phase:

The distance measurement phase achieves a commendable accuracy rate of approximately 93%. This high accuracy underscores the system's ability to precisely calculate the distance between the camera and the detected vehicles, leveraging advanced techniques based on the lens and light equation. The accuracy achieved in this phase is pivotal for accurate speed estimation in subsequent analysis.

Speed Measurement Phase:

In the speed measurement phase, the system exhibits varying levels of accuracy, with reported values of 95%, 81%, and 95.4%. These accuracy percentages highlight the system's effectiveness in estimating the speed of moving vehicles based on distance differentials between frames and FPS information. While the majority of instances achieve high accuracy levels, slight discrepancies may be observed in certain scenarios, warranting further investigation for optimization.

Overall, the results analysis corroborates the efficacy of the developed system in performing detection, distance measurement, and speed measurement tasks. The achieved accuracies validate the effectiveness of the implemented methodologies and algorithms, laying a solid foundation for enhancing road safety and traffic management through real-time analysis of vehicle movements.

4.6 Objectives Achieved

The objectives outlined in the thesis have been successfully achieved through meticulous research and implementation. Firstly, data collection from local Bangladeshi roads was conducted, ensuring a diverse dataset representative of real-world scenarios. Using the OpenCV library, the collected video data was effectively preprocessed, setting the stage for subsequent analysis. The YOLOv5 model was then trained and fine-tuned with the custom dataset, achieving a commendable detection accuracy of 80.1% in identifying vehicles within the video stream

Next, a robust distance measurement model was developed leveraging the principles of light refraction and lens equations. This model exhibited high accuracy, achieving a rate of approximately 93% in calculating vehicle distances from the camera. Additionally, a tracking algorithm was implemented to assign unique IDs to vehicles and measure their speed based on distance differentials between frames. Despite some variability, the speed measurement component demonstrated accuracies of 95%, 81%, and 95.4%, highlighting its effectiveness in estimating vehicle speeds.

The analysis of the system's performance across its various components provided valuable insights into its capabilities and areas for further optimization. Overall, the successful accomplishment of these objectives demonstrates the feasibility and effectiveness of the developed system in accurately detecting, tracking, and measuring the speed of vehicles in real-world road scenarios. These achievements lay a solid foundation for advancing research in road safety and transportation management, contributing to enhanced traffic monitoring and management efforts.

4.7 Financial Analysis and Budget

4.7.1 Budget Allocation:

Funds are earmarked for equipment, transportation, and permits for video data acquisition. Expenses related to publishing research papers, attending conferences. Expenses related to testing model in real world scenario like fuel cost, buying GPU etc.

Table 4.2: Estimated Budget of This Thesis

Budget Component	**Estimated Cost**
Software Acquisition	5,000tk
Dataset Acquisition and Preparation	20,000tk
Research Related Expense	10,000tk
Miscellaneous Expense	15,000tk
Total Estimated Budget	**50,000tk**

4.8 Conclusion

In conclusion, the chapter on implementation, results, and discussions encapsulates the culmination of extensive research, development, and analysis aimed at realizing the objectives outlined in the thesis. Through meticulous implementation of various methodologies and algorithms, including data collection, vehicle detection, distance measurement, and speed estimation, the developed system has demonstrated commendable capabilities in addressing the challenges of road safety and transportation management.

The results obtained from each phase of the system's implementation provide valuable insights into its performance and effectiveness. Despite encountering challenges and variability in accuracy, particularly in the speed measurement phase, the system has showcased promising capabilities in accurately detecting vehicles, measuring distances, and estimating speeds in real-world road scenarios.

Furthermore, the discussions surrounding the results delve into the intricacies of system performance, identifying potential areas for optimization and further research. By critically analyzing the achieved objectives, discussing limitations, and proposing avenues for future enhancements, the chapter sets the stage for continued advancements in road safety technology.

Overall, the chapter on implementation, results, and discussions serves as a comprehensive examination of the developed system, highlighting its strengths, weaknesses, and potential for future improvements. The insights gained from this analysis lay the groundwork for continued research and innovation in the field of road safety and transportation management, ultimately contributing to safer and more efficient road networks.

CHAPTER V

Societal, Health, Environment, Safety, Ethical, Legal and Cultural Issues

5.1 Intellectual Property Considerations

In the realm of technological innovation, intellectual property considerations play a pivotal role in safeguarding the rights and interests of creators and innovators. Within the context of this thesis, intellectual property considerations are paramount in protecting the novel methodologies, algorithms, and technologies developed for enhancing road safety and transportation management.

The advancements made in vehicle detection, distance measurement, and speed estimation entail valuable intellectual property that may be subject to various forms of protection, including patents, copyrights, and trade secrets. It is imperative to assess the potential intellectual property implications of the developed system and its components to ensure proper recognition and protection of the innovation.

Furthermore, intellectual property considerations extend beyond legal protections to encompass ethical and cultural dimensions. Ethical considerations dictate the responsible use of intellectual property, ensuring that innovations are deployed in a manner that benefits society while minimizing potential harm. Cultural sensitivities may also influence intellectual property considerations, particularly in diverse socio-cultural contexts where norms and values may differ.

As such, this section delves into the complexities of intellectual property considerations within the scope of the thesis, addressing legal, ethical, and cultural dimensions to ensure the responsible and equitable use of innovative technologies for the betterment of society. By navigating these considerations thoughtfully, the thesis aims to contribute to the advancement of road safety technology while upholding ethical principles and respecting cultural diversity.

5.2 Ethical Considerations

Ethical considerations are paramount in the development and deployment of technologies aimed at improving road safety and transportation management. Within the framework of this thesis, ethical considerations encompass a range of principles and concerns related to the responsible use of technology, the protection of individual rights and privacy, and the promotion of societal well-being.

One key ethical consideration revolves around the potential implications of vehicle surveillance and monitoring systems on individual privacy rights. As the developed system involves the detection and tracking of vehicles in real-time video streams, safeguards must be implemented to protect the privacy and anonymity of individuals captured within the footage. This entails adhering to data protection regulations, anonymizing personally identifiable information, and obtaining informed consent where necessary.

Furthermore, ethical considerations extend to the broader societal impact of the technology. The deployment of advanced surveillance and monitoring systems should be accompanied by transparent governance mechanisms and accountability frameworks to ensure that the benefits of the technology are equitably distributed and that potential negative consequences, such as surveillance creep or discriminatory practices, are mitigated.

Additionally, ethical considerations encompass the equitable access to and use of road safety technologies. It is essential to address disparities in access to technology, particularly in marginalized communities, to ensure that the benefits of road safety innovations are realized by all members of society. Moreover, efforts should be made to minimize the potential for technology-driven biases or discrimination, such as through the equitable distribution of enforcement measures and the promotion of inclusive design principles.

By exploring and addressing these ethical considerations, the thesis aims to foster a responsible and ethical approach to the development and deployment of road safety technologies. Through thoughtful consideration of ethical principles and values, the thesis seeks to contribute to the advancement of road safety initiatives while upholding individual rights, promoting societal well-being, and fostering inclusivity and equity.

5.3 Safety Considerations

Ensuring safety is paramount in developing technologies for road safety. Risks must be mitigated, and hazards minimized to ensure the system's reliability and the protection of road users. Rigorous testing and validation are vital to verify the system's accuracy and effectiveness. Furthermore, the system's resilience in adverse conditions must be assessed, and measures implemented to enhance robustness. Additionally, the system's impact on human behavior and decision-making should be considered to ensure it promotes safe practices without inadvertently encouraging risk-taking. By addressing these safety considerations comprehensively, the thesis aims to develop a system that prioritizes safety while improving road safety and transportation management.

5.4 Legal Considerations

Legal compliance is imperative throughout the lifecycle of road safety technology development and deployment. Adhering to data protection regulations, such as the General Data Protection Regulation (GDPR) in the European Union or equivalent laws in other jurisdictions, ensures the ethical handling of sensitive data collected by the system, safeguarding individuals' privacy rights. Moreover, compliance with traffic laws and regulations governing surveillance technologies, including permits and permissions for camera deployment, ensures the system's lawful operation and acceptance within legal frameworks. Establishing liability frameworks, including indemnification clauses and risk mitigation strategies, clarifies accountability in case of system-related incidents or accidents, fostering transparency and trust among stakeholders. By navigating these legal considerations comprehensively, the thesis aims to develop a system that upholds legal standards while advancing road safety and transportation management initiatives, thus promoting legal compliance, trust, and societal acceptance of the technology.

5.5 Impact of the Project on Societal, Health, and Cultural Issues

The project's development and deployment of road safety technologies have significant implications for various societal, health, and cultural dimensions. Here's an analysis of its impact:

Societal Impact:

The project's focus on enhancing road safety contributes to the overall well-being of society by reducing the risk of accidents and improving traffic management.

By deploying advanced surveillance and monitoring systems, the project aims to create safer road environments for all road users, including drivers, pedestrians, and cyclists.

Improved road safety can lead to a reduction in traffic congestion, travel time, and economic costs associated with road accidents, thereby enhancing the quality of life for individuals and communities.

Health Impact:

The project's efforts to mitigate road accidents can have a significant impact on public health by reducing the incidence of injuries and fatalities resulting from traffic collisions.

By promoting safe driving practices and providing real-time feedback on vehicle speeds, the project contributes to the prevention of road accidents and associated injuries, thus safeguarding public health and well-being.

Furthermore, the project's focus on reducing traffic congestion and promoting efficient traffic flow can lead to improvements in air quality and respiratory health by reducing vehicular emissions and pollution levels.

Cultural Impact:

The deployment of road safety technologies may influence cultural attitudes and behaviors related to road safety and driving practices.

By raising awareness of road safety issues and promoting responsible driving behaviors, the project aims to foster a culture of safety and accountability within communities.

Additionally, the project's engagement with diverse cultural contexts and communities ensures that road safety interventions are tailored to local norms, values, and preferences, fostering greater acceptance and integration of the technology within cultural frameworks.

In conclusion, the project's impact on societal, health, and cultural issues is multifaceted, encompassing improvements in road safety, public health, and cultural attitudes towards driving practices. By addressing these dimensions holistically, the project aims to create safer and more inclusive road environments that benefit individuals, communities, and societies at large.

5.6 Impact of Project on the Environment and Sustainability

The project's endeavors in enhancing road safety and transportation management also have implications for the environment and sustainability. Here's an analysis of its impact:

Environmental Impact:

The implementation of road safety technologies contributes to the reduction of traffic accidents and congestion, which can lead to a decrease in vehicular emissions and pollutants emitted into the atmosphere.

By optimizing traffic flow and reducing instances of idling and stop-and-go traffic, the project aims to minimize fuel consumption and greenhouse gas emissions, thereby mitigating its environmental footprint.

Additionally, the project's focus on efficient transportation management may lead to the adoption of eco-friendly transportation modes, such as public transit, cycling, and carpooling, further reducing environmental impacts associated with individual vehicle use.

Sustainability Impact:

The project's emphasis on road safety and efficient traffic management aligns with broader sustainability goals aimed at creating more sustainable and livable cities.

By promoting safer and more sustainable transportation practices, the project contributes to the long-term sustainability of urban infrastructure and the well-being of communities.

Furthermore, the integration of advanced technologies and data-driven approaches in transportation management enhances the resilience and adaptability of transportation systems to evolving environmental challenges, such as climate change and resource constraints.

In conclusion, the project's impact on the environment and sustainability is significant, encompassing reductions in vehicular emissions, improvements in traffic efficiency, and the promotion of sustainable transportation practices. By aligning road safety initiatives with sustainability objectives, the project aims to create more environmentally friendly and resilient transportation systems that benefit both present and future generations.

CHAPTER VI

Addressing Complex Engineering Problems and Activities Associated with speed estimation of front vehicle

6.1 Introduction

The development and implementation of road safety technologies present a myriad of complex engineering challenges that require innovative solutions and rigorous methodologies. Within the scope of the current thesis, several intricate engineering problems have been identified and addressed to achieve the project's objectives effectively.

6.2 Complex engineering problems associated with the current research

Table 6.1: Complex engineering problems associated with the current research

Attributes	Characteristics
Depth of Knowledge	Depth of knowledge in computer vision technique and image processing like extracting image resizing, measuring height, width, in pixels, and lighting model of refractive rays
Range of conflicting requirement	Try to use pixel height and real height ratio to measure the distance of a vehicle from camera point was conflicting challenge. Using lighting model to find the distance was challenging
Depth of analysis required	The depth of analysis required for this thesis involves thorough examination and evaluation of various components, including data collection methods,

	algorithm development, system integration, and societal implications.
Familiarity of the problem	There are many other familiar technique of measuring speed like radar based, laser based. But computer vision based is very rare. And in this thesis methodology is very rare like distance measurement technique.
Extend of applicable codes	The research and development process, including the design, implementation, and evaluation detection, distance and speed measurement model maintains the code of conduct of software engineering, machine learning, and data handling.
Extend of stakeholder involvement and conflicting requirements	The research uses datasets which is gathered by this researcher to engage stakeholders and advance understanding of image and video handling in the field of speed measurement.
Interdependence	The algorithmic development of speed measurement model, dataset preparation, performance evaluation metrics, and ethical considerations are highly interdependent in speed measurement tasks.

6.3 Complex engineering activities associated with the current research

The current research involves a series of complex engineering activities aimed at developing and implementing a robust speed estimation system using monocular vision sensors. These activities include data collection, algorithm development, system integration, testing, and validation, as well as performance optimization. Additionally, considerations for societal, legal, and ethical implications are addressed throughout the research process. These interdisciplinary efforts require expertise in computer vision, machine learning, optics, image processing, and systems engineering to overcome challenges and achieve accurate and reliable speed estimation results

Table 6.2: Complex engineering activities associated with image restoration

Resources	Cameras or sensors for capturing video footage of road traffic in various conditions. Financial support for equipment, software licenses, dataset acquisition, and research personnel. High-performance computers or servers for processing large volumes of video data and training machine learning models.
Level of interaction	Interactions within the research endeavor encompass various stakeholders, including researchers, peers, senior professionals, and notably, my supervisor. Working closely with my supervisor has been pivotal, offering invaluable mentorship, guidance, and oversight to ensure the project's adherence to academic standards and alignment with its objectives.
Innovation	The innovation showcased in this thesis lies in the introduction of a groundbreaking methodology for enhancing speed measurement accuracy. Through the development of a novel patch-based framework, the research presents an innovative approach to optimize speed estimation systems. Departing from conventional methods, this strategy

	leverages advanced principles of patch-based processing to refine speed measurement algorithms without the need for complex CNN aggregation.
Consequences for society and environment	The adoption of the novel speed measurement methodology carries significant implications for society and the environment. By enhancing accuracy, the system aids in curbing road accidents, thus promoting safer roads and bolstering community well-being. Moreover, optimized traffic flow resulting from precise speed measurements can lead to reduced fuel consumption, lower emissions, and diminished environmental impact. Additionally, the methodology supports law enforcement efforts, fostering compliance with traffic regulations and fostering a culture of responsible driving, thereby contributing to a more sustainable and harmonious societal and environmental landscape
Familiarity	By using lighting model for distance measurement, this thesis introduces a unique technique for speed measurement which is more cost effective and not many familiar.

6.4 Conclusion

In conclusion, the field of speed measurement combines computer vision, deep learning, and image processing. It is clearly both exciting and difficult. This chapter has covered the intricate activities and contemporary issues in the sector. Even with the advancements, some artifacts still need to be addressed with appropriate postprocessing methods. The issue might be avoided if sufficient hardware resources were provided.

CHAPTER VII

Conclusions

7.1 Summary

The thesis, "Speed Estimation of Front Vehicle Using Monocular Vision Sensor," focuses on developing a robust system for accurately estimating the speed of the front vehicle utilizing monocular vision sensor data. The research begins with a comprehensive review of existing methods and technologies in speed estimation and identifies limitations in traditional approaches, particularly regarding overtaking scenarios on two-lane roads. Through meticulous data collection from local Bangladeshi roads and the subsequent preprocessing and annotation of video datasets, the project lays the foundation for algorithm development and training. Utilizing advanced machine learning techniques, including the YOLOv5 model, the system achieves high accuracy in vehicle detection, providing bounding box information and labels for each detected vehicle. A novel distance measurement model is then developed, incorporating principles of optics and image processing to accurately calculate the distance between the camera and the front vehicle. This model accounts for factors such as perspective distortion, calibration errors, and variations in vehicle sizes, ensuring precise distance estimations. Subsequently, a tracking algorithm is implemented to monitor the movement of vehicles over consecutive frames, enabling the assignment of unique identifiers and facilitating speed measurement calculations. By analyzing the distance traveled by the front vehicle over time and multiplying it by the frame rate, the system effectively estimates the vehicle's speed, providing valuable information for safe overtaking maneuvers and traffic management. The thesis also addresses various societal, health, environmental, safety, ethical, legal, and cultural considerations associated with the deployment of road safety technologies, underscoring the importance of responsible technology development. In conclusion, the research contributes to the advancement of road safety technology, offering an innovative solution for speed estimation that can enhance road safety and transportation management in diverse settings.

7.2 Limitations

Speed measurement accuracy relies on distance estimation, which in turn depends on the bounding box height provided by the YOLO model. However, inconsistencies in bounding box heights for the same object at the same distance may occur, leading to errors in distance measurement and subsequent speed estimation.

Acquiring the speed of the reference vehicle, necessary for calibrating the system, may pose challenges in certain scenarios, potentially affecting the accuracy of speed estimation.

Variations in the height of vehicles such as motorbikes, vans, rickshaws, and bicycles, particularly when ridden by individuals of different heights, can result in different bounding box sizes in the YOLO model. This variability may introduce additional errors in distance and speed estimation.

The accuracy of the YOLO model, upon which the speed estimation system relies, may not be sufficiently high. Missed detections or inaccuracies in vehicle detection by the YOLO model can impact the overall performance and reliability of the speed estimation system.

The limited size of the dataset used for training and testing the speed estimation system may constrain the system's ability to generalize to diverse real-world scenarios, potentially limiting its effectiveness in practical applications.

These limitations highlight areas for further research and improvement in the development and implementation of the speed estimation system, emphasizing the need for robust solutions that can address variability and uncertainties inherent in real-world traffic environments.

7.3 Future Works

Improved Distance Measurement Techniques: To enhance distance measurement accuracy, future research could involve acquiring additional photos of vehicles at known distances and developing a polynomial equation to account for variations in focal length based on bounding box height. This approach would improve the system's ability to accurately estimate distances under varying conditions.

Enhanced Detection Models: Further efforts can be directed towards training the YOLO model with larger and more diverse datasets or exploring alternative detection models to improve the accuracy of vehicle detection. By enhancing detection capabilities, the speed estimation system can provide more reliable and precise speed estimates, thereby enhancing overall road safety.

Integration with Autonomous Vehicles: Integrating the developed speed estimation system with autonomous vehicle technologies holds promise for reducing accidents and improving traffic flow. By providing real-time speed information of front vehicles, autonomous vehicles can make informed decisions to ensure safe and efficient navigation, ultimately contributing to the advancement of autonomous driving systems.

Development of Alert Systems: Real-time speed estimation of front vehicles can be utilized to develop alert systems that warn drivers about potential hazards, particularly in overtaking scenarios on two-lane roads. By analyzing the relative speeds of vehicles approaching from opposite directions, the system can provide alerts to drivers, indicating whether it is safe to overtake or not, thereby reducing the risk of accidents and promoting safer driving practices.

Integration with Traffic Management Systems: The speed estimation system can be integrated into existing traffic management systems to provide valuable insights for traffic monitoring and control. By incorporating real-time speed information into traffic flow optimization algorithms, authorities can better manage traffic congestion and improve overall road safety and efficiency.

Exploration of Advanced Technologies: Future research could explore the integration of advanced technologies such as LiDAR and radar sensors to complement vision-based speed estimation systems. By combining multiple sensor modalities, the system can improve accuracy and reliability, particularly in challenging weather conditions or low-visibility environments.By pursuing these avenues of future work, the speed estimation system can evolve into a more robust, accurate, and integrated solution for enhancing road safety and transportation management in diverse real-world scenarios.

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