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A Study of Vehicle-Pedestrian Jay-walk Interactions at Median Road Locations in Bangladesh: Using IMAGE RECOGNITION AND IMAGE PROCESSING TECHNIQUES

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It is hereby declared that this thesis/project report or any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

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Dedication

We dedicate this thesis to our beloved families.

To our fathers, for their unwavering support and encouragement.

To our sisters, for always believing in us and motivating us to strive for excellence.

To our uncles, for their wise guidance and constant inspiration.

And especially, to our mothers, whose love, sacrifices, and endless patience have been the foundation of all our achievements.

This work would not have been possible without their continuous support and love.

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Abstract

Pedestrian safety remains a global concern as a significant number of traffic-related injuries and fatalities involve pedestrians. Factors such as uncontrolled traffic flow, mid-block crossings, and inadequate road safety infrastructure exacerbate this issue. According to the Federal Highway Administration (FHWA), these elements are particularly prevalent in densely populated and poorly regulated urban environments. In Bangladesh, the capital city of Dhaka consistently reports the highest traffic fatality rates, underscoring the urgency of addressing pedestrian safety in developing countries. Although developed nations like the United States, Ireland, and Greece have conducted extensive studies on jaywalking in controlled traffic scenarios, limited research has focused on underdeveloped countries, where traffic is often mixed and unpredictable, making the problem more complex.

This study investigates the influence of the distance and speed of oncoming vehicles on jaywalking decisions across three urban zone types: industrial, residential, and commercial. These zones were chosen for their diverse traffic characteristics and pedestrian usage patterns. Dashcam footage from vehicles traveling in these areas was used to collect data. The selected locations include Bangla-motor and Gulshan (commercial zones), Mirpur and Banani (residential zones), and Gazipur and Tejgaon Industrial Area (industrial zones). Advanced image recognition techniques, specifically the YOLOv8 (You Only Look Once) machine learning model, were employed to detect jaywalking behavior. The model also measured the speed and distance of approaching vehicles, providing precise and real-time data.

To analyze jaywalking patterns, Kernel Density Estimation (KDE) plots were generated, allowing a visual understanding of pedestrian crossing behavior. Statistical analyses, including two-sample t-tests for both equal and unequal variance, were used to compare the speed and distance of oncoming vehicles across different zones and timeframes, specifically during morning, evening, and off-peak hours.

The findings reveal significant variations in pedestrian and vehicular behavior based on the zone and time of day. Industrial zones recorded the highest vehicle speeds during weekdays, averaging 16.41 km/h, reflecting the urgency and high volume of traffic in these areas. Conversely, residential zones exhibited the highest vehicle speeds on weekends, averaging 26.18 km/h, likely due to reduced weekday congestion and higher recreational movement. Regarding crossing distances, pedestrians in residential zones maintained the longest distance from oncoming vehicles during off-peak hours on weekdays (7.48 m). On weekends, the residential zones also showed the greatest crossing distance during morning peak hours (8.05 m), suggesting a more cautious approach by pedestrians during specific periods.

This study provides valuable insights for urban planners and policymakers aiming to enhance pedestrian safety. The detailed behavioral patterns observed across different zones and timeframes highlight the need for tailored interventions. Recommendations include the installation of safer pedestrian crossings, implementation of traffic-calming measures, stricter enforcement of jaywalking laws, and the integration of intelligent traffic management systems. Additionally, improving road safety infrastructure in high-risk areas such as industrial zones could significantly reduce pedestrian-vehicle conflicts. These findings serve as a foundation for developing comprehensive road safety strategies not only in Bangladesh but also in other developing countries facing similar challenges.

Keywords: Pedestrian Safety, Jaywalking Behavior, Traffic Analysis, Road Safety Infrastructure, YOLOv8, Traffic Dynamics, Urban Zones, Developing Countries

CHAPTER ONE: INTRODUCTION

1.1 Background

Globally, approximately 1.19 million people lose their lives in traffic-related incidents every year, with pedestrians accounting for a significant proportion of these fatalities [26]. In Bangladesh, pedestrian deaths represent 32% of total traffic-related fatalities, a figure that is approximately 10% higher than the global average [27]. This disproportionate burden highlights a critical gap in road safety measures for vulnerable road users. In 2022, the Road Safety Foundation (RSF) recorded 6,829 traffic incidents in Bangladesh, resulting in 12,615 injuries and 7,713 fatalities. Among the divisions, Dhaka reported the highest fatality count, with 1,841 deaths [1]. As one of the most densely populated cities globally, Dhaka struggles with inadequate road infrastructure, poor traffic management systems, and limited pedestrian facilities [2]. These shortcomings have made jaywalking—a dangerous and illegal act of crossing roads without adhering to traffic rules—a pressing concern in the city.

The lack of pedestrian infrastructure, such as sidewalks, pedestrian overpasses, and designated crossings, exacerbates this issue. The prevalence of jaywalking contributes to pedestrian vulnerability and further complicates the already chaotic traffic situation [3]. Given this scenario, there is an urgent need to analyze jaywalking behavior in Dhaka, focusing on how pedestrian crossing infrastructure and the dynamic nature of mixed traffic conditions influence crossing decisions.

Jaywalking is a significant safety concern as it not only jeopardizes pedestrians' lives but also disrupts overall traffic flow. Numerous studies have investigated the factors influencing illegal road crossing behavior and pedestrian strategies during crossings. For example, research shows that pedestrians often wait at roadsides or medians for opportunities to cross, with their patience and attention diminishing over time, increasing their likelihood of risky crossings [14]. Furthermore, the absence or misuse of designated facilities plays a crucial role in pedestrian crashes, with studies indicating that 80% of such incidents occur when pedestrians use undesignated crossings [15].

Comparative studies in developed countries highlight behavioral differences in pedestrian crossings at marked versus unmarked crosswalks. For instance, a 2003 study in Dublin, Ireland, observed that a significant proportion of pedestrians chose to jaywalk rather than wait for the green light at signalized intersections, prioritizing convenience over safety [8]. Similarly, a 2012 study in Greece revealed a strong preference for crossing outside marked facilities,

1 Key Facts

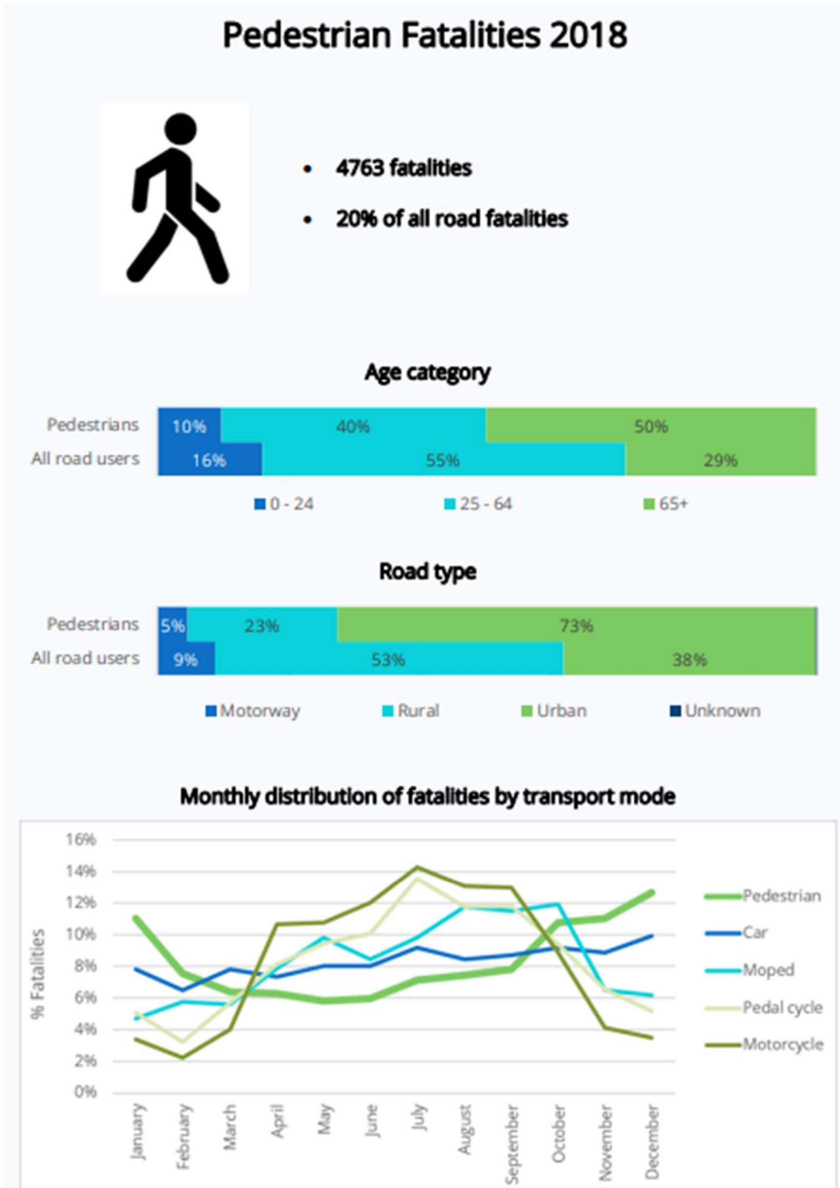

Fig 1.1: *Pedestrian Fatalities 2018*

highlighting how human behavior adapts to infrastructure availability [10]. Other studies have explored factors like pedestrian crossing speed [7], gap acceptance [11, 18, 19], and route selection [12, 13], but research remains limited in contexts with mixed and dynamic traffic conditions, such as those found in developing countries.

Bangladesh's traffic ecosystem, characterized by a mix of motorized and non-motorized vehicles, chaotic road usage patterns, and varying traffic laws enforcement, presents unique challenges. Understanding jaywalking behaviors within this context requires examining specific influences, such as vehicular speed and distance from pedestrians, across different urban zones like commercial, residential, and industrial areas.

Technological advancements, particularly in machine learning and computer vision, have proven to be valuable tools for studying traffic safety. For instance, deep learning algorithms have been employed to predict pedestrian behavior at signalized intersections [16] and estimate the distance between pedestrians and approaching vehicles [28]. YOLO (You Only Look Once), a state-of-the-art image recognition tool, has also seen widespread adoption in traffic safety research. YOLOv5, for example, has been successfully used for real-time jaywalking detection at intersections [11], while YOLOv8—the latest version—has demonstrated capabilities in vehicle speed detection [17]. These studies underscore the potential of integrating technology into traffic management and safety.

Despite these advancements, there remains a gap in the practical application and analysis of these tools in high-risk, mixed-traffic environments, especially in underdeveloped settings like Dhaka. Therefore, this study seeks to bridge that gap by investigating the role of vehicular speed and distance in influencing jaywalking decisions. It focuses on three distinct urban zones—commercial, residential, and industrial—across peak and off-peak hours. By leveraging YOLOv8 and employing statistical methods like t-tests, this research aims to provide actionable insights that can inform policy changes, infrastructure improvements, and targeted safety interventions to mitigate pedestrian risks in Dhaka.

1.1.1 Urbanization and the Rise of Pedestrian Risks

As the city of Dhaka continues to undergo rapid urbanization, its pace of infrastructural development has not kept in tandem with the expansion and this has led to a metropolis which is not geared towards the increasing demands of its inhabitants. Containing a population of over 22 million people in the metropolitan zone, Dhaka is on brink of insanity as people tend to get stuck in doses of traffic congestion every single day. Even for their own kind, the people who walk, there are numerous challenges posed: for example, no proper place to cross the road, very bad footpaths and the roads themselves filled up with moving cars. All the same, this gets worse when one considers the current economic and social standing of the city, in which walking still remains a popular means of transport for a large number of people.

With pedestrian facilities not available, the level of road crossing without using the designated crossings has risen sharply. Anyone who has to cross the road at these points is likely to run the gauntlet of a line of cars zooming past with very little space in between all dashed lines of cars. This is not just an issue of how hard it is to take the inconvenience; the transport systems are inefficient that it breeds such behavior. For example, in most regions, elevated sidewalks and tunnels which offer alternatives to dangerous streets and would cater for people crossing the road are either non-existent or in a state of disrepair. Also, people’s attitude over road safety and control mechanisms such as traffic law enforcement is very weak, making it easy for people to practice use the road at no crossings without fear of sanctions.

1.1.2 Global Perspectives on Pedestrian Safety

The problem of jaywalking is not only present in Dhaka. In the USA, Ireland, and Greece, specific behavioral aspects of crossing roads have been explored widely and adds to knowledge about safety on the roads. In the USA for instance, researchers have studied how street layouts, traffic light patterns, and the age of the pedestrians affect their behavior in crossing the streets. Convenience to the pedestrians has also been documented in Ireland where surveys established that pedestrians will usually jaywalk even if there are crossings that are less than a few meters away. Research studies in Greece have also found that pedestrians tend to avoid walking with the appropriate provision of road crossing facilities by walking to other unmarked places to cross the road.

Nevertheless, the perspectives in developed countries and in a developing country differ. In most developed nations traffic systems are more controlled and the presence of enforcement officers and walking facilities is always guaranteed. Consequently, to understand the behaviour of people in the act of `jay walking` the environment is fairly supportive. In contrast traffic in a place like Dhaka is not only much different but also more volatile as it is a cross between cars, very few if not no traffic management and poor road construction. Such contrasts make it imperative to conduct more research that focuses on the situation of pedestrianism in developing countries.

1.1.2 Research Gaps in Jaywalking Studies

Studies of pedestrian behaviour have been conducted extensively in developed countries but the understanding of jaywalking behaviour in the streets of developing countries remain scanty. Most of the available studies have looked at crossing speeds, gap acceptance, and adherence to traffic control devices. For example, Tezcan et al. (2019) studied midblock crosswalks, focusing on who crossed how and the impact of design and traffic on this behavior. In the same line, Mukherjee and Mitra (2019) studied expected pedestrian crossing speeds and gap acceptance at traffic-controlled intersections highlighting the traffic conditions measurement and responses by the pedestrians crossing the road.

These studies prove important, but usually suffer from the drawback of studying in developed nations that have all the basic facilities including cross walking paths and pedestrain signals in the cities which are not the case with Dhaka and many other third world urban centers. Besides, they also ignore the concept of traffic as a social factor which involves a lot of mixing including chaotic movement of vehicles, which is common in most of the developing countries. In Dhaka, for example, the roads are used by pedestrians, cars, buses, motorbikes, bicycles, and rickshaws all of different speeds and movements. This variety makes it hard for the pedestrian to make decisions and enhances the dangers that come hand in hand with – jaywalking.

Another research gap is the limited use of technology to study pedestrian behaviors in most developing countries. Computer vision and machine learning in particular have greatly advanced traffic safety research within the past few decades through detection and tracking of pedestrians in video footage in real time. However, the application of such technologies has largely been limited to laboratory settings in developed countries. As a result, this study seeks to address this issue by analyzing jaywalking behavior in Dhaka using YOLOv8, one of the most recent image recognition models.

1.2 Objective of the Study

The present study is targeted at analyzing the factors leading to jaywalking behavior among pedestrians in Dhaka, with emphasis on traffic speed, distance from vehicles, and specific areas where such behavior differs. The specific objectives are:

1. To compare the rates of jaywalking in residential, commercial and industrial areas.
2. To evaluate the relationship between traffic speed, distance and pedestrians' behavior.
3. To understand the variations in incidence of jaywalking over time, that includes the peaks and off peak periods as well as the days of the week.
4. To develop strategies to increase safety for pedestrians and reduce the occurrences of jaywalking, based on sound evidence.

1.2.1 Theoretical Framework

Several theoretical perspectives can be employed to study the behavior of jaywalking, as in, risk perception, decision-making, as well as behavioral economics. As they walk, pedestrians constantly assess the risks vs. benefits of crossing at that particular point and time. This is done with the understanding that factors such as traffic velocity, distance and movement of vehicles and physical urgency all contribute to the decision. The concept of 'gap acceptance' is useful in explaining jaywalking behavior. Gap acceptance is the time or distance gap within which a pedestrian feels it is safe to cross the street amid oncoming traffic. Studies have established that gap acceptance tends to be influenced by environmental and individual characteristics. For example, the younger generations of pedestrians are more likely to accept smaller gaps in traffic compared to older ones who may focus upon the safety of doing so. In high-speed traffic conditions, the tendencies of pedestrians are to wait for much larger gaps hence a higher risk perception. On the other hand, low traffic on the road tactically reduces the risk thus more attempts to cross the road are made. All these behaviors are also subject to cultural and contextual influences. In contrast, in Dhaka which has limited crossing facilities, the tendency to take risks is more pronounced as pedestrians tend to incline more to the speed and comfort of crossing than safety.

1.2.2 Technological Advancements in Pedestrian Behavior Research

The study of pedestrian behavior has received new horizons due to the introduction of advanced technologies like computer vision and machine learning. Among them all, the model is devoted to one of the measurements of behavior — jaywalking — and is able to do that without the loss on the speed, which is regarded as the greatest speed accuracy. Thus, YOLOv8, can even be used while analyzing a video or footage in real time to, for example, spider out vehicular speed, pedestrian reach, and crossing gauges among other factors.

In this study, analysis of jaywalking behavior in Dhaka is carried out using YOLOv8. Kernel Density Estimation (KDE) plots and two-sample t-tests are also used in the study and they add to the analytical value of the study. presenting the statistics of distances and speeds of jaywalking in the form of diagrams with the use of KDE plots helps to present the statistics effectively and to find unusual characteristics. It is also possible with the use of two sample-t tests, to ascertain if the difference between certain conditions is significant or not, for example, the difference between residential and commercial areas or between weekdays and weekends. These approaches in turn give a complete picture of the jaywalking activities from different perspectives.

1.3 Scope of Research

The scope of this research encompasses:

The present study is targeted at analyzing the factors leading to jaywalking behavior among pedestrians in Dhaka, with emphasis on traffic speed, distance from vehicles, and specific areas where such behavior differs. The specific objectives are:

1. To compare the rates of jaywalking in residential, commercial and industrial areas.
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4. To develop strategies to increase safety for pedestrians and reduce the occurrences of jaywalking, based on sound evidence.

1.4 Significance of the Research

This research is significant for several reasons:

1. **Pedestrian Safety:** Understanding jaywalking behaviour can help reduce pedestrian-related accidents by informing the design of safer urban infrastructure and traffic management policies.
2. **Urban Planning:** The findings can guide urban planners in developing more effective pedestrian crossing facilities and traffic control measures.
3. **Traffic Management:** Insights into traffic speed and distance factors influencing jaywalking can enhance traffic flow models and lead to better traffic management strategies.
4. **Technological Application:** The study demonstrates the application of advanced image processing and machine learning techniques in real-world traffic safety research, showcasing their potential to address complex urban mobility challenges.

1.5 Outline of Thesis

The thesis is organized into six chapters as follows:

Chapter 1: Introduction

- Background of the study

- Objective of the study
- Scope of research
- Significance of the research
- Outline of the thesis

Chapter 2: Literature Review

- Review of existing studies on pedestrian behaviour and jaywalking
- Impact of urban infrastructure on pedestrian safety
- Technological advancements in traffic safety research

Chapter 3: Data and Methodology

- Site selection and data collection methods
- Equipment setup and data recording procedures
- Image processing techniques and model training
- Statistical analysis methods

Chapter 4: Analysis and Model Development

- Detailed analysis of jaywalking behaviour and traffic conditions
- Development of predictive models for jaywalking
- Validation and reliability checks

Chapter 5: Results and Interpretation

- Presentation of key findings from the data analysis
- Interpretation of results in the context of urban traffic management
- Discussion of policy implications and recommendations

Chapter 6: Conclusions and Recommendations

- Summary of the study and its key contributions
- Recommendations for future research and policy development
- Final thoughts on the study's impact on pedestrian safety and urban planning

These sections will collectively provide a comprehensive overview of the research, from the initial motivation and objectives to the detailed analysis and final conclusions, ensuring a coherent and thorough presentation of the study's findings and their implications.

CHAPTER TWO: LITERATURE REVIEW

2.1 Pedestrian behavior and Perception

Research has shown that pedestrian environments can significantly influence walking behaviors and perceptions of safety. A study conducted by Kweon et al. (2021) investigated the effects of pedestrian environments on parents' walking behavior, their perception of pedestrian safety, and their willingness to let their children walk to school. The study found that the presence of a sidewalk, buffer strip, and street trees affected parents' decision to walk, their willingness to let their children walk to school, and their perception of the pedestrian environment as safer for walking. Another study developed a pedestrian safety poster targeting jaywalking using several theoretical constructs from well-established behavioral change models. A questionnaire survey was administered to pedestrians to gauge their perceptions of the poster. This highlights the importance of understanding pedestrian behavior and perceptions in addressing jaywalking and improving pedestrian safety. (Byoung-Suk Kweon, 5 August 2021)

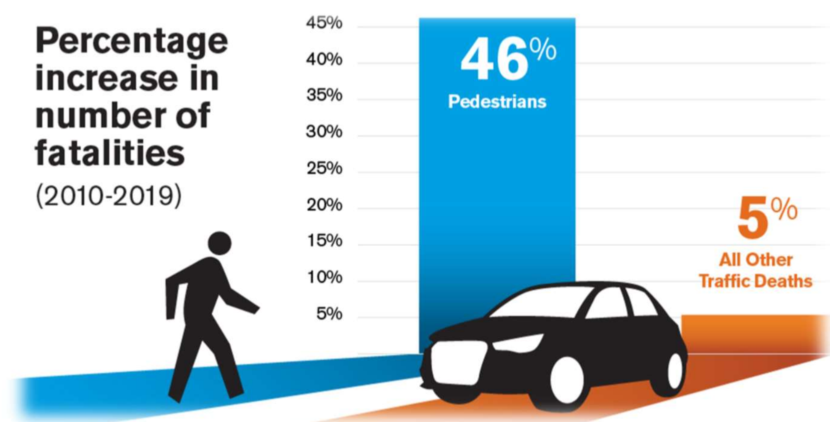
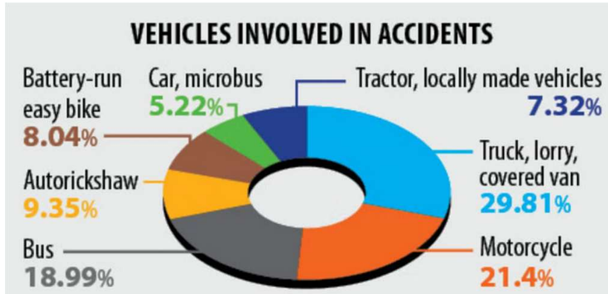


Fig 2.1: *Pedestrian Traffic Fatalities by State: 2019 Preliminary Data*

2.2 Bangladesh Perspective:

Approximately 25,000 lives are lost in road accidents each year in Bangladesh.-BJKS(2023).On average, 64 individuals lose their lives daily in road accidents across the country.-The Daily Star(2023).



YEAR-WISE ROAD CRASHES AND DEATHS

YEAR	ACCIDENTS	DEATH
2019	5516	7855
2018	5514	7221
2017	4979	7397
2016	4312	6055

SOURCE: BANGLADESH JATRI KALYAN SAMITY

Fig 2.2: Source: Bangladesh Jatri Kallyan Samiti, a road safety organization

2.3 Pedestrian Attributes

Factors that affect J-walking behavior in a pedestrian.

Age:

Age is a significant factor in pedestrian behavior. Younger individuals may be more agile and quick, allowing them to navigate through traffic more efficiently. On the other hand, older individuals may require more time to cross streets and may be more cautious, impacting their behavior as pedestrians. (Ravishankar, 29 August 2022)

Gender:

Gender can also influence pedestrian behavior. Some studies suggest that men and women may exhibit different behaviors when navigating as pedestrians. For example, men might be more likely to jaywalk or cross against a signal, while women might be more likely to wait for the signal to change before crossing. (Charitha Dias, Oct 2022)

Physical Ability:

Physical ability can greatly influence pedestrian behavior. Individuals with physical disabilities may require more time to cross streets and may need accessible infrastructure, such as ramps and audible signals. (al, 2023)

Familiarity with the Area:

Pedestrians who are familiar with an area may behave differently than those who are not. They might know the best routes, the timing of traffic signals, and locations of crosswalks, which can influence their navigation and crossing behaviors. (Kweon, 2021)

Purpose of Travel:

Pedestrians who are familiar with an area may behave differently than those who are not. They might know the best routes, the timing of traffic signals, and locations of crosswalks, which can influence their navigation and crossing behaviors. (Kweon, 2021)

Crowd size:

The size of the crowd can significantly impact pedestrian behavior. In larger crowds, individuals often conform to the behavior of the group, which can lead to phenomena like "herding" or "crowd panic." In contrast, individuals in smaller groups or walking alone may have more freedom to choose their path and pace. Additionally, high pedestrian volumes can lead to slower walking speeds and increased congestion. (M. Haghani, 8 August 2019).

Cultural backgrounds:

Cultural background can also influence pedestrian behavior. In some cultures, jaywalking might be common, while in others, people might strictly adhere to traffic rules. Similarly, the level of courtesy shown to other pedestrians or to drivers can vary between cultures. For example, in some cultures, it's common to yield to others, while in others, it might be more common to assert one's own right of way. This is a broad generalization, and individual behaviors can vary widely within any culture. (Mimi Tian, 5 September 2022)

Alcohol use:

Alcohol use can significantly impact pedestrian behavior. Intoxication can impair judgment, coordination, and reaction times, leading to risky behaviors such as jaywalking or crossing against signals. It can also affect the pedestrian's ability to perceive and respond to threats in the environment, such as approaching vehicles. Therefore, alcohol use is a major concern when considering pedestrian safety. (Aqshems Nichols, Summer 2023)

Social psychology:

Social psychology can greatly influence pedestrian behavior. The presence of others can affect an individual's decision-making process and risk-taking behavior. For example, individuals are more likely to cross a road in risky situations if others are also crossing. This is known as the "herd effect." Similarly, social norms and societal rules, such as traffic regulations, can influence whether individuals comply with crosswalk signals and other traffic controls. Peer pressure and the desire to conform can also play a role in shaping pedestrian behavior. (Anna Sieben, June 7, 2017).

2.4 Illegal behaviors:

J-walking, or illegal pedestrian road behaviors, poses risks in urban areas. This includes crossing streets without designated areas, ignoring signals, and walking on roads with sidewalks. (Legal Dictionary. (2023). Jaywalking)

Process of crossing in various locations:

Jaywalking is the act of crossing a roadway when it is unlawful to do so. This includes crossing between intersections, as well as crossing at a crosswalk equipped with a signal, without waiting for the proper indication that it is safe to do so. (Legal Dictionary. (2023). Jaywalking)

Statistical analysis of violation:

Pedestrian fatalities and injuries due to road traffic accidents are a significant issue globally, as highlighted by the World Health Organization (WHO, 2018). Pedestrians, being vulnerable road users, are disproportionately represented in traffic accident statistics in many countries (e.g., Afukaar et al., 2003, Hijar et al., 2003, Ariffin et al., 2010, Mabunda et al., 2008, Mohan et al., 2009, Naci et al., 2009, Zegeer and Bushell, 2012). This problem is particularly severe in low- and middle-income countries (WHO, 2018). In Bangladesh, classified as a least developed country by the OECD (2019), pedestrian-involved collisions constitute between 37% and 73% of all accidents in metropolitan areas and about 56% in non-metropolitan areas.

It has been observed that 41% of pedestrian-involved collisions occur while crossing roads and 39% while walking on the road (Mahmud et al., 2009). Jaywalking is the act of crossing a roadway when it is unlawful to do so. This includes crossing between intersections, as well as crossing at a crosswalk equipped with a signal, without waiting for the proper indication that it is safe to do so. (Mithun Debnath, Jun 2021)

Parameters of crossing:

The parameters of crossing, particularly in the context of jaywalking, encompass several factors. These include the location of crossing, the speed of crossing, and adherence to traffic signals. (Papadimitriou, 2016)

Presence of other pedestrians on the opposite side of the road:

The presence of other pedestrians on the opposite side of the road can influence the behavior of. (Papadimitriou, 2016)

2.5 Influence mechanism of factors:

Understanding the factors influencing jaywalking behavior is essential for urban traffic safety. Thompson and Garcia (2019) [37] explore various sociological and psychological factors that lead to jaywalking, including rush behaviors and lack of awareness about traffic rules. Another study by Kim et al. (2021) [38] focuses on the urban design elements that inadvertently promote jaywalking, such as inadequate pedestrian infrastructure and poor placement of crosswalks. These studies underscore the multifaceted nature of jaywalking behavior and the need for comprehensive strategies to address it.

Traffic flow and Congestion:

Traffic flow and congestion are critical in understanding urban mobility challenges. A study by Wang and Zhang (2020) explores the relationship between traffic density and congestion, providing insights into optimal traffic flow management techniques. Additionally, Patel's research (2023) on congestion patterns in metropolitan areas offers a comprehensive analysis of peak and off-peak traffic flow dynamics, suggesting that improved traffic signaling can alleviate congestion and enhance overall traffic efficiency.

Speed of Vehicle:

Vehicle speed plays a crucial role in urban traffic dynamics and pedestrian safety. Research by Johnson et al. (2021) highlights the impact of vehicle speed on the reaction time of both drivers and autonomous vehicle systems. The study emphasizes that lower speeds are associated with increased reaction times and reduced severity of accidents. Furthermore, Smith and Lee (2022) analyze traffic flow data to demonstrate that moderating vehicle speeds in urban areas can significantly decrease the incidence of traffic accidents, particularly those involving pedestrians.

Distance of Vehicle from Pedestrian:

The distance between the vehicle and pedestrians is crucial for safety and is monitored using sensors and LiDAR technology. The presence of the vehicle in far, near, or middle lanes can also influence traffic flow and pedestrian safety. (Muhammad Mobaidul Islam, 27 Aug 2021)

Vehicle presence in far, near or middle lane:

Understanding the position and movement of surrounding vehicles, especially their presence in far, near, or middle lanes, is crucial for AVs. The research by Patel and Kumar (2021) focuses on the detection and classification of vehicles based on their lane positions using advanced image processing techniques. Their findings suggest that identifying the lane position of vehicles can significantly enhance traffic flow prediction and collision avoidance strategies in AV systems.

Further, the study by Gomez and Lee (2023) on highway driving scenarios illustrates how AVs utilize a combination of camera and radar data to determine the lane positions of other vehicles, aiding in lane-changing decisions and maintaining safe distances. This research underscores the importance of real-time lane position detection in ensuring the safety and efficiency of AV navigation.

Education Level:

Various studies have explored pedestrian road crossing strategies and the influences of key determining factors on illegal crossing behavior. For instance, Marisamynathan and Vedagiri (2018) found that education level, occupation, and trip purpose significantly affected crossing behavior. (Marisamynathan and Vedagiri (2018)) [1].

Waiting Time:

Mukherjee and Mitra (2019) identified factors such as age, education level, trip purpose, and waiting time at intersections as promoting traffic law violations. (Mukherjee and Mitra, 2019) [2].

Unmarked vs Marked Crosswalks:

Pedestrian behaviors at unmarked crossings differ significantly from those at marked crosswalks; jaywalkers tend to be more cautious, looking both ways and hurrying to cross during larger gaps [4]. Several factors influence jaywalking locations, including the presence of bus stops and average annual daily traffic. Understanding how drivers yield to jaywalkers compared to other crossing pedestrians, as well as jaywalking gap acceptance and oncoming traffic speeds, is crucial from an operations and planning perspective [4]. Observational surveys showed that walkers prefer making illegal crossings instead of waiting for the green light [5].

Minimize Walking Distance:

Also, pedestrians prefer to cross from outside the crossing facility to minimize their walking distance [6]. Therefore, safety interventions on street-crossing behavior are necessary since they positively change crossing behavior [7]. Therefore, safety interventions targeting street-crossing behavior are necessary as they can positively influence crossing habits.

Attention Span:

Pedestrian-related factors contribute significantly to road accidents, with pedestrians being at fault in 59% of cases, drivers in 32%, and both in 9% (Alam et al., 2011; Hasib et al., 2012) [14]. Pedestrians often wait at the roadside or median to cross, and their attention diminishes with increased waiting time (Hamed, 2010; Cherry et al., 2010) [15]. The location of road crossing facilities also plays a crucial role in pedestrian accidents, with about 80% of accidents occurring when pedestrians cross without using designated facilities (Gitelman et al...2012; Kadali et al...2013; BRTA 2016-2017) [16].

Crossing Speed:

Several previous studies in the past have examined pedestrian crossing behaviors, crossing speed [2], gap acceptance [7-8-9], and trip route choice [10-11]. However, few of them have considered jaywalking gap acceptance with respect to traffic speed events in 3rd world countries.

2.6 Urban Infrastructure:

Recent studies have continued to explore the intricacies of pedestrian behaviour and safety. For instance, a study by Hussain et al. (2021) [21] emphasized the role of urban infrastructure in influencing pedestrian safety. They found that well-designed pedestrian facilities, such as overpasses and underpasses, significantly reduce the incidence of jaywalking and related accidents. Another study by Carmichael et al. (2021) [17] highlighted the impact of traffic law enforcement on pedestrian behaviour, demonstrating that stricter enforcement leads to a reduction in illegal road crossings and improved overall traffic safety.

The use of advanced technologies such as machine learning and computer vision in traffic safety research has gained traction. For example, a study by Zhang et al. (2022) [18] utilized deep learning algorithms to predict pedestrian crossing behaviour at signalized intersections, showing high accuracy in identifying potential jaywalking incidents. This aligns with the current study's use of YOLOv8 for image recognition and processing to analyse pedestrian jaywalking incidents in Dhaka.

2.7 Image Segmentation and Speed Estimation:

The methodology used in this study to process images and estimate speed incorporates the latest image recognition methods, supplemented by the YOLOv8 model and other specific algorithms developed for this research. Detailed information about the data processing techniques, including the YOLOv8 model and the specific algorithms used, is provided below. This section offers a comprehensive description of the algorithms, techniques, and tools employed, along with a detailed description of the implementation process, thus providing a clear and detailed methodological framework for conducting the current study.

Image Processing Techniques:

An important step in this research is the image processing. The initial step of the program is to identify jaywalkers and non-jaywalkers in the video recorded by the dashcam. Object detection is accomplished using YOLOv8, an effective deep-learning model that is fast and efficient at detecting pedestrians and vehicles.

Jaywalk and Non-jaywalk Detection:

YOLOv8Model:

The YOLOv8 model is trained on a dataset of pedestrians and vehicles that consist of images. The model is categorized as real-time as it responds to events as they occur in the images. YOLOv8 utilizes an architecture as a single network for both the prediction of bounding boxes and the class probability from the full image in a single pass. We used the RSUD20K (https://github.com/hasibzunair/RSUD20K/releases/tag/v1) pre-trained yolov8.pt model to detect jaywalks and non-jaywalks since this pre-trained model is trained with the local vehicles of Dhaka, Bangladesh.

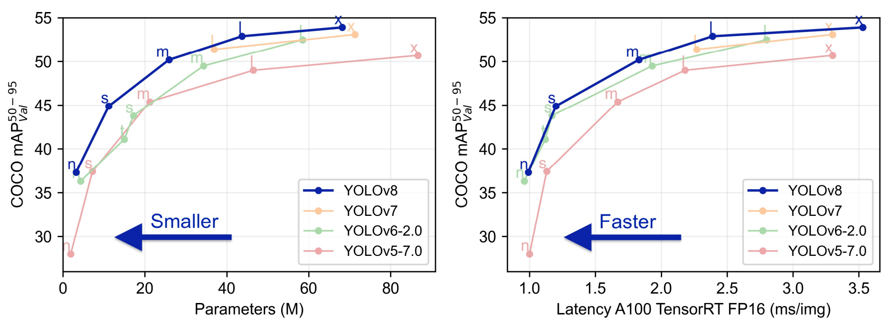


Fig 2.3: Yolov8 Efficiency Improvement

Several Python libraries and frameworks were utilized in this study to implement the image processing and machine learning algorithms:

TensorFlow and Keras:

TensorFlow:

TensorFlow is a machine learning introductory framework developed by Google, extensively applied for constructing and training various deep learning models. It offers a broad range of implementations in frameworks for creating machine learning applications and options for different neural networks and training methods.

Model Deployment:

TensorFlow's versatility extends to model deployment, allowing the trained models to be deployed in different environments, from cloud servers to edge devices. This capability is crucial for real-time applications where the model needs to operate efficiently on embedded systems.

Kera's:

Kera's is an open-source Neural Network API designed to be user-friendly and run on top of TensorFlow. It helps in the construction and training of deep learning models in an easier manner. Keras provides a simple and appropriate way of designing and training deep learning models. Its features include defining new layers and call-backs, making the fine-tuning of the training process possible, which is essential for jaywalking detection and classification tasks.

OpenCV:

Open-Source Computer Vision Library:

OpenCV is a collection of algorithms and functions implemented as computer programs, primarily used for real-time computer vision. It has been applied in different image analysing applications such as image splitting, object identification, and video analytics.

Pre-processing and Augmentation:

OpenCV is used for tasks such as resizing, normalization, and data augmentation of the frames taken from the given video. These pre-processing steps involve feature extraction and normalization, critical for fine-tuning data inputs for the model and protecting against variations within inputs.

Post-processing:

OpenCV is also used in the post-processing of the model output, where annotations and masks such as the bounding box and segmentation masks of the detected jaywalkers are drawn. These final steps make the results more easily visualized and easier to analyse further.

scikit-learn:

Model Evaluation:

scikit-learn is an open-source library for Python that provides tools for implementing machine learning algorithms. It includes easy interfaces for data mining and data analysis and the integration of algorithms for distance estimation, such as the decision tree algorithm. The decision tree model built using scikit-learn has metrics and tools to measure its performance, which are employed to measure performance indicators such as accuracy, precision, and recall.

Cross-validation:

Scikit-learn's cross-validation tools are used to assess the decision tree model and minimize the risk of overfitting. This is accomplished through a process known as cross-validation, where a dataset is divided into multiple folds, and the model is trained on different sets for improved generalization.

NumPy and Pandas:

NumPy:

NumPy enhances Python's capabilities by providing multi-dimensional arrays for homogeneous data and a wide variety of mathematical functions. It is used for numerical computations, including vectors and matrices, which are essential for carrying out machine learning calculations and assessing collected data.

Pandas:

Pandas is a highly efficient data manipulation tool built on Python. It provides data structures and functions for processing numerical tables and time series. Pandas is used for handling data recorded from the video and the car's GPS system. It includes tools for data cleaning and transformation, assisting in organizing and merging data.

YOLO (You Only Look Once) models have been widely adopted in various traffic safety applications due to their speed and accuracy. YOLOv8, the latest iteration, has shown promise in enhancing traffic monitoring systems. A recent study by SM Shaqib (2023) [23] demonstrated the use of YOLOv8 for vehicle speed detection. Their implementation in a busy urban setting revealed that YOLOv8 could effectively manage real-time traffic data, providing actionable insights for traffic management authorities.

These advancements underscore the importance of integrating technology with urban planning and policy-making to address the complex issue of jaywalking in densely populated urban areas. The critical role of advanced technologies, such as image recognition and deep learning models, in improving pedestrian safety is evident. They highlight the need for thoughtful urban planning that incorporates comprehensive traffic safety measures to protect pedestrians and optimize urban mobility.

Despite the extensive literature on pedestrian road crossing behavior and pedestrian safety, very few of these studies have dived into comprehensive detail of the main factors that a pedestrian decides before crossing a road legally or illegally, every pedestrian before crossing looks left or right checks the distance of the closest traffic vehicle and its estimated speed of approach.

This study aims to comprehensively investigate how the distance and speed of oncoming traffic jointly influence jaywalking decisions across different urban zones (residential, commercial, industrial) in a developing country context. By elucidating these factors, the research seeks to uncover nuanced insights into pedestrian behavior, thereby informing targeted interventions to enhance pedestrian safety and urban planning strategies.

The findings of this study hold implications for urban planners, policymakers, and transportation engineers tasked with improving pedestrian safety and optimizing urban mobility in developing countries. By identifying zone-specific variations in jaywalking behavior, interventions can be tailored to address the unique challenges posed by different urban contexts, ultimately contributing to safer and more pedestrian-friendly cities.

CHAPTER THREE: DATA COLLECTION

3.1 Site Selection

The study focuses on various zones in Dhaka, Bangladesh, categorized into commercial, residential, and industrial areas. The selected sites were chosen based on the following criteria:

Commercial Zones: High pedestrian and vehicular traffic. Data was collected from commercial hubs such as Bangla-motor (307) and Gulshan (124) as outlined in the area plan (2022-2035) for RAJUK with 1,570 jaywalks recorded in Bangla Motor and 636 in Gulshan. These areas are characterized by mixed land use with significant pedestrian activity.

Residential Zones: Predominantly residential areas with moderate pedestrian traffic. Data was collected from Mirpur (67), Bashundhara R/A (164) as outlined in the area plan (2022-2035) for RAJUK, which exhibit typical residential characteristics with 389 jaywalks recorded in Mirpur, 954 in Bashundhara R/A. These areas have lower traffic volumes compared to commercial zones but notable jaywalking behavior.

Industrial Zones: Areas characterized by industrial activities and heavy vehicle movement. Data was collected from Gazipur (136) and Tejgaon Industrial Area (279) as outlined in the area plan (2022-2035) for RAJUK with 518 jaywalks recorded in Gazipur and 1,063 in the Tejgaon Industrial Area. These zones typically have lower pedestrian traffic but are critical for understanding jaywalking in diverse urban settings.

Table 3.1: Data collection summary

Zone	**Area**	**No. of Pedestrians Jaywalking/Area**	**No. of Pedestrians Jaywalking/Zone**
Commercial Area	Bangla Motor	1570	2206
	Gulshan	636	
Residential	Mirpur	389	1900
	Uttara	557	
	Bashundhara R/A	954	
Industrial	Gazipur	518	1581
	Tejgaon	1063	

3.2 Data Distribution

Jaywalk Count:

- Indicates the total number of jaywalking incidents observed in each area type:
  - Weekend: Residential (937), Commercial (1286), Industrial (577)
  - Weekday: Residential (963), Commercial (920), Industrial (1004)

Area Types and Metrics:

- Data is categorized by **Residential**, **Commercial**, and **Industrial** areas. For each area type, two metrics are reported:
  - **Distance**: Likely the distance jaywalkers traveled (e.g., meters).
  - **Speed**: Likely the speed at which jaywalkers moved (e.g., meters/second).

Statistical Measures:

- The rows under each area type show the following:
  - **Minimum Value**: The smallest recorded value.
  - **First Quartile (Q1)**: The value below which 25% of the observations fall.
  - **Median**: The middle value of the dataset.
  - **Third Quartile (Q3)**: The value below which 75% of the observations fall.
  - **Maximum Value**: The largest recorded value.

Table 3.2: Data distribution for box plot of jaywalking for weekend and weekday

Weekend						
Jaywalk Count	**937**		1286		**577**	
	Residential		Commercial		Industrial	
	Distance	**Speed**	**Distance**	**Speed**	**Distance**	**Speed**
Minimum Value	0.053	0.021	0.007	0.037	0.405	0.018
First Quartile	5.857	9.550	3.645	4.836	5.040	7.009
Median	7.302	15.841	5.046	8.045	6.666	12.080

Third Quartile	8.189	24.327	6.291	13.230	8.000	20.316
Maximum Value	12.644	34.347	13.946	53.323	12.992	55.000
Weekday						
Jaywalk Count	**963**		**920**		**1004**	
	Residential		Commercial		Industrial	
	Distance	**Speed**	**Distance**	**Speed**	**Distance**	**Speed**
Minimum Value	0.680	0.008	0.690	0.049	0.382	0.073
First Quartile	1.073	5.009	5.000	7.000	4.393	7.000
Median	6.559	9.405	6.976	13.000	7.000	15.000
Third Quartile	7.631	20.608	8.000	19.098	8.000	23.000
Maximum Value	11.559	70.000	11.716	41.775	13.782	55.000

Weekday and Weekend Jaywalking Boxplots

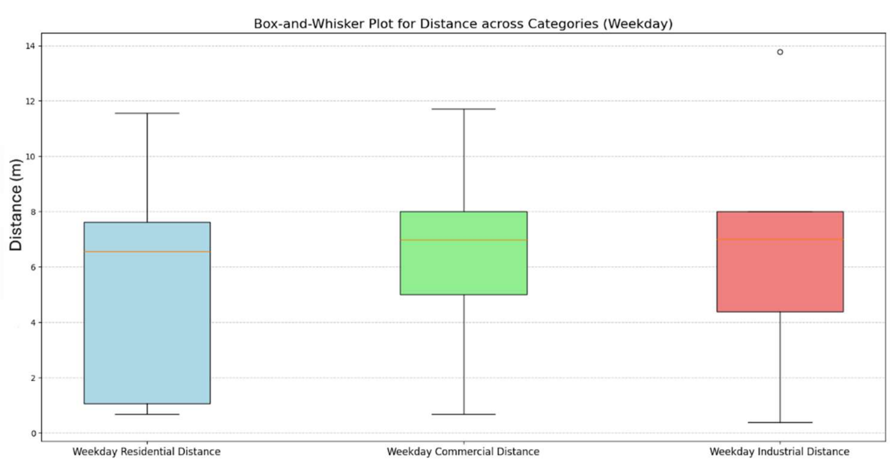


Fig. 3.1. Weekday Jaywalking Boxplot Distance(m)

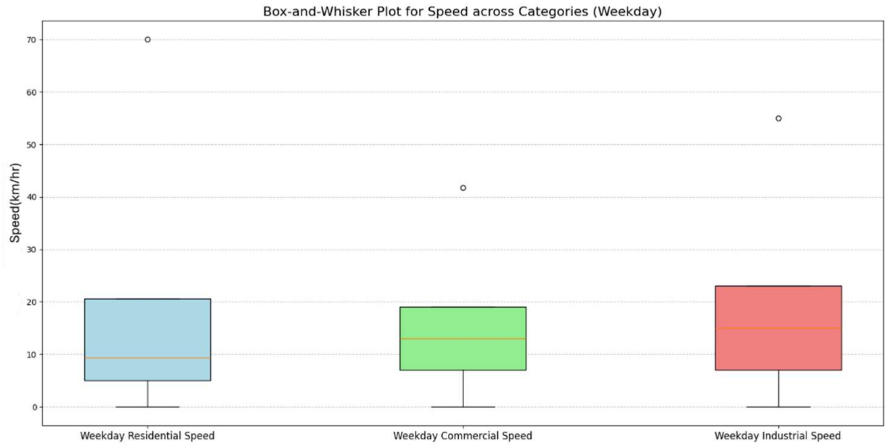


Fig. 3.2: Weekday Jaywalking Boxplot Speed(km/hr)

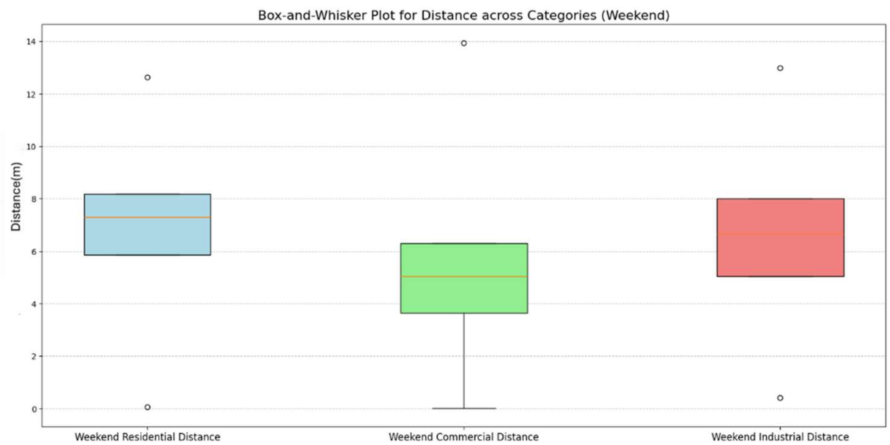


Fig. 3.3: Weekend Jaywalking Boxplot Distance(m)

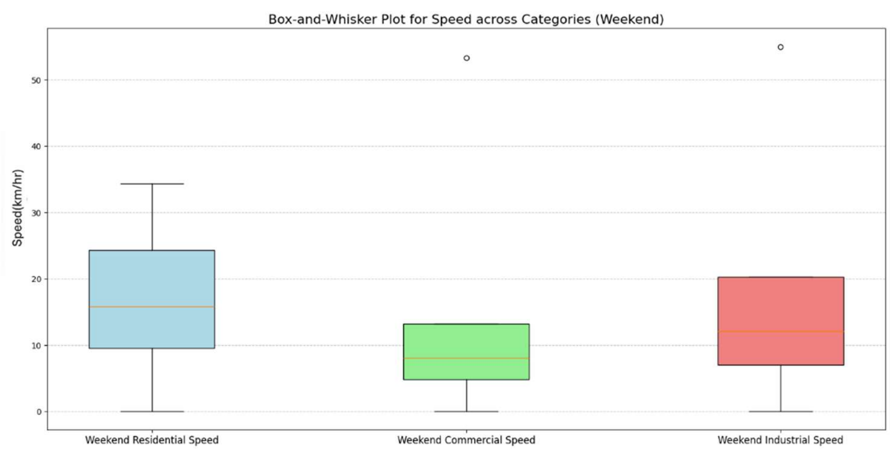


Fig. 3.4: Weekend Jaywalking Boxplot Speed(km/hr)

3.3 Equipment Setup

A dashcam was set up in the vehicle (1999 Toyota Premio Corona Sedan 4,560 mm in length and 1,695 mm in width) used for the research at an optimal angle, calibrated to provide a clear view of the road ahead. The equipment and setup include the following:

Dashcams: Full HD dashcams were installed at the front of the car to record clear footage of pedestrian interactions with the research vehicle. The dashcams have a field of view of 130 degrees, which needs to be considered during distance estimation.

GPS Devices: A GPS unit was mounted in the vehicle to capture real-time speed and location data. The GPS system determines speed by repeatedly measuring the vehicle's position and calculating how far the vehicle moved over a specific time period, then dividing that distance by the time to give the speed of the vehicle. This ensures accurate synchronization of video footage with geographical coordinates and speed information.

Computing Equipment: A PC with a decent graphics processing unit (GPU- NVIDIA RTX 3070ti) was used to process the video data.

Image Processing Software: YOLOv8, an advanced image recognition model, was employed to detect pedestrians and estimate their distance from oncoming vehicles. Custom-developed algorithms were used to integrate video data with GPS information.

Data Storage Solutions: Secure and high-capacity storage devices were used to store raw and processed data, with regular backups to ensure data integrity and availability for analysis.

Data Recording

Data was collected during different times of the day, including peak, off-peak, and evening hours. The process included the following steps:

Study Parameters

The study parameters were meticulously defined to ensure accurate and comprehensive data collection and analysis. These parameters reflect the dynamic and complex nature of pedestrian and vehicular interactions in Dhaka’s urban traffic environment. Below is an expanded description of the parameters:

Data Collection Period

- **Duration:** The data collection spanned nearly six months, from October 19, 2023, to April 16, 2024.

The goal of this data collection protocol is to complete the data collection within the time frame of six months, October 2023 – April 2024, with the allowance of the variation of week days and week ends. The vehicle was positioned within the lane to the middle of the roadway to enhance the chances of capturing the instances of pedestrians crossing the road inappropriately. The recordings were done at three different time intervals:

- **Morning Peak (7:00 AM - 10:00 AM):** Period characterized with high number of people on foot as well as vehicles as works and schools opening hours approaches.
- **Evening Peak (5:00 PM - 8:00 PM):** Activity levels similar to that of morning peak but with the addition of traffic for leisure.
- **Off-Peak Hours (11:00 AM - 3:00 PM):** Traffic less congested although there were more speeding cars.
- Recording of videos was carried out regardless of whether it was raining or shining. People count, their characteristics, amount of traffic, and other relevant details in the surroundings were recorded in addition to the video files.

- **Purpose:** This extended timeframe allowed the study to capture variations in traffic and pedestrian behavior across different seasons and months, providing a holistic view of jaywalking patterns.
- **Weather Considerations:** The chosen period included both the dry season and pre-monsoon transitional period, as weather can significantly influence pedestrian road-crossing behavior.

Vehicle Specifications

- **Make and Model:** The Toyota Premio Corona 1999 Sedan was selected due to its typical representation of an average vehicle operating in Dhaka.
- **Dimensions:**
    - **Length:** 4,560 mm (179.5 inches)
    - **Width:** 1,695 mm (66.7 inches)
    - **Height:** 1,410 mm (55.5 inches)
- **Relevance:** Understanding the dimensions of the vehicle was crucial for analyzing pedestrian behavior in relation to vehicle proximity and size perception.
- **Field of View (FOV):** The car's dashcam positioning leveraged its size to maintain an optimal angle for clear visibility, minimizing blind spots in footage.

Speed Distribution

- **Speed Range:** The vehicle operated at speeds varying from 0 to 90 km/h, consistent with urban traffic conditions in Dhaka.
- **Urban Speed Variation:**

    - **Peak Hours:** Speeds were often reduced due to high traffic density and congestion.
    - **Off-Peak Hours:** Vehicles could travel faster, offering insights into pedestrian decisions during varying traffic speeds.
- **Significance:** The speed range captured the dynamic nature of mixed traffic environments, including slow-moving rickshaws, motorcycles, buses, and high-speed private cars.

Traffic Conditions

- **Time of Day:** Data was collected during different periods of the day:
    - **Morning Peak Hours:** High pedestrian and vehicle volume during commute times.
    - **Evening Peak Hours:** Increased congestion with a mix of commuters and recreational traffic.
    - **Off-Peak Hours:** Less crowded conditions with more spaced-out vehicle movement.
- **Days of the Week:** The study considered both weekdays and weekends to evaluate differences in jaywalking behavior based on typical weekday routines versus more relaxed weekend activities.

Zone Coverage

- **Locations:** The study covered three distinct types of zones to reflect varying urban dynamics:
    - **Commercial Zones:** Areas like Bangla Motor and Gulshan, characterized by heavy pedestrian activity and business-related traffic.
    - **Residential Zones:** Areas like Mirpur and Banani, with moderate traffic flow and community-driven pedestrian activity.
    - **Industrial Zones:** Areas like Gazipur and Tejgaon Industrial Area, with high-speed traffic and fewer pedestrian-friendly infrastructures.
- **Zone-specific Dynamics:** The choice of zones provided insights into how different environments impact jaywalking decisions, allowing for targeted road safety interventions.

Pedestrian Interactions

- **Jaywalking Behavior:** Focused on pedestrians' decisions to cross roads in unauthorized areas.

- **Vehicle-Pedestrian Proximity:** Data captured included the distance between vehicles and pedestrians during crossings to measure gap acceptance.
- **Speed Perception:** Observations accounted for how vehicle speed influenced pedestrian crossing decisions, offering insights into risk-taking behavior.
- **7. Traffic Mix**
- **Diverse Vehicle Types:** The study incorporated data from various vehicle types, including private cars, buses, motorbikes, and non-motorized vehicles like rickshaws.
- **Relevance:** The mixed traffic scenario of Dhaka posed unique challenges and allowed for a comprehensive analysis of pedestrian-vehicle interactions under unpredictable conditions.

3.4 Data Segmentation

An explorative study design that encompassed both qualitative and quantitative approaches was adopted. Analysis of the data in this case combined the use of computational tools and quantitative analysis. This approach allowed the investigators to assess both the objective components such as things measured in distances and speeds, and also the subjective part which, in this case, is the choice making behavior among pedestrians. The course of the research was structured as follows:

Recorded videos were segmented based on the zones (commercial, residential, industrial) and the time of day. The segmentation process involved:

Using Coordinates: The coordinates of the jaywalk locations were used to segment the data into jaywalks in residential, commercial, and industrial zones according to the Detailed Area Plan (2022-2035) for the RAJUK Area.

Zone Designation: Each area was segmented into its designated zone, ensuring accurate data categorization for analysis.

3.5 Data Processing and Annotation

Data processing involved developing an image recognition framework using Python (YOLOv8) to accurately detect jaywalk and non-jaywalk incidents. The process included:

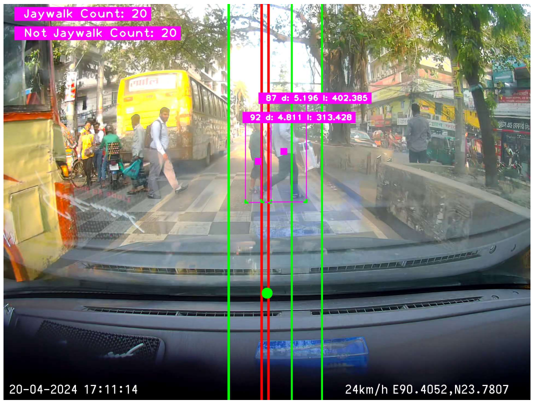


Fig. 3.5: Jaywalk Detection

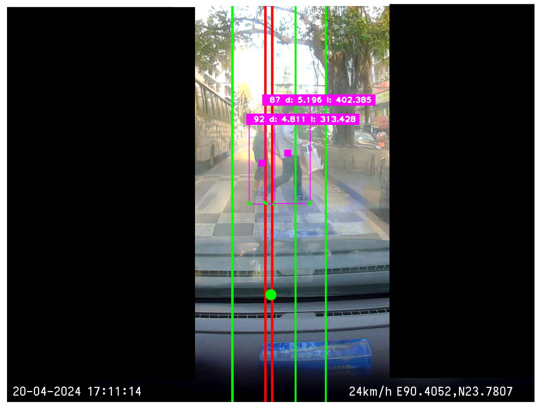


Fig. 3.6: Mask

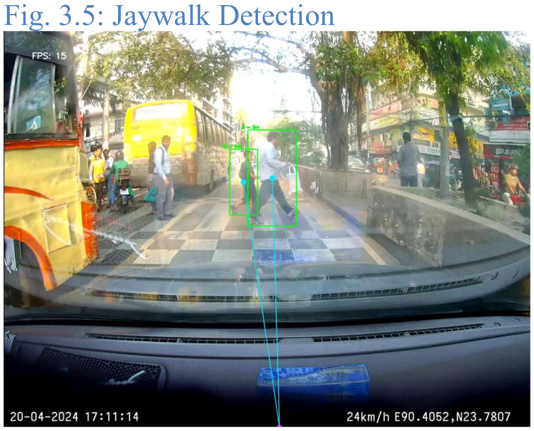


Fig. 3.7: Distance Estimation

Fig. 3.8: OCR mask

Comment: screenshots in this data is done under a zebra crossing need to change

The resulting figures [figure1] shows the jaywalk detection methodology where the green lines are attempted to jaywalk lines and the red lines are committed jaywalk. If a person passes the green lines from the outside, then not-jaywalk incremented by 1 and a screenshot saved in gallery. If the same person crosses the red line, then it is counted as jaywalk and another screenshot taken.

[fig. 3.6] shows masks implemented on both sides of the video to stop erroneous detection of pedestrians not interested in jaywalking

[fig. 3.7] is the distance estimation methodology where the pixel height of the bounding box is taken and the pixel length from the center bottom point of the image to the center point of the detected pedestrian, these two variables are ultimately used in decision tree to predict the distance.

[fig. 3.8] a full mask is given over the video for easy OCR capture of the data that is being recorded at the bottom of the image.

Image Recognition: The framework detected jaywalking incidents and extracted annotated screenshots of these incidents, including data to extract speed using GPS data and pixel length for distance estimation.
Data Annotation: Annotated video data was further processed and imported into spreadsheets for easier data analysis. This step ensured that the data was well-organized and ready for statistical analysis.

3.6 Data Collection Equipment

The instrumented vehicle study enabled real-time recording of speed, location, and other relevant data using a data acquisition system. The specific equipment and setup were as follows:

Instrumented Vehicle: The vehicle used in this study was a Toyota Premio, privately owned. The dashcam had a built-in GPS where all information about vehicle position and speed data was displayed and video recorded on a micro-SD card. This data was later transferred to an Excel database using OCR software.
Selected Routes: The study team selected routes based on jaywalking characteristics, covering 17 road locations distributed among different zones using the Detailed Area Plan (2022-2035) for the RAJUK Area.

CHAPTER FOUR: METHODOLOGY

4.1 Model Training:

Dataset Preparation: The first is the acquisition of a dataset with images of pedestrians and vehicles as the input data. The coordinate values of the objects within each image are marked using rectangular frames or bounding boxes. This is because the strength of the model as well as the range within which it is going to be most effective largely depends on the quality and variety of the data in question.

Data Collection: Images are gathered from places in Dhaka, Bangladesh for this specific assignment. The collected images are manually labeled to ensure that the generated dataset is used in creating and or training the models.

Data Augmentation: To expand the size and diversification of the dataset, augmentation techniques on the images include rotation, scaling, flip page, etc. Augmentation is useful in enhancing the generalization of the model since the model gets a variety of different distributions of the same items.

Training the YOLOv8 Model: The YOLOv8_model will be trained on a prepared dataset. That means taking the images and their annotations through the model to optimize its parameters. In the act of training, after every epoch, its performance will be checked on a validation set in order to reduce the errors of detection.

Hyperparameter Tuning: Model hyperparameters, including learning rate, batch size, and the number of epochs, need to be tuned for optimal performance. The basic idea of hyperparameter adjustment is an experimentation process concerning which values work better in giving the best possible detection accuracy.

Loss Function: The loss function to be minimized in training the YOLOv8s contains the sum of classification loss, localization loss, and confidence loss. Backpropagation will calculate gradients, and gradient descent will optimize that loss function.

4.2 Real-Time Detection:

Video Processing: The video footage captured by the dashcam is fed into a trained YOLOv8 model. Their resolution was 1920X1440. In the model, jaywalkers are detected and classified in real-time, allowing analysis in the act and making responses in real-time. Real-time processing capacity is very important in applications where timely detection and intervention matter.

Frame-by-Frame Analysis:

The video frames are thus processed one by one, and the model considers each frame on its own. The frame-by-frame analysis provides a consistent and accurate detection throughout the video.

Latency Optimization:

Programmatic techniques to reduce latency are followed so that the model can work effectively in real time. Optimizations of model architectures and reducing the complexities of the computations, along with hardware acceleration, are some of the latency optimization techniques.

4.3 Segmentation with Mask R-CNN:

Instance Segmentation:

Mask R-CNN is a neural network architecture for instance segmentation, as it can detect and segment each object in an image individually.

For jaywalkers, Mask R-CNN generates segmentation masks, which outline the exact pixels belonging to each particular jaywalker and provide pixel accuracy.

This will enable precise location where you can identify the bounds precisely for every jaywalker within the video frames captured.

Tracking Across Frames:

To segment the jaywalkers, the next step is to track these across multiple frames in the video.

OpenCV provides functions for tracking. For instance, algorithms are available from Simple Online and Realtime Tracking, such as the SORT algorithm, or other algorithms for multi-

object tracking. These algorithms assign unique IDs to each detected jaywalker and track their movement through different frames.
Tracking algorithms in OpenCV preserve the identities of jaywalkers so that each entity has consistent tracking in a video sequence—at least, he/she whom somebody occludes by another person for some moments or there is an event of appearance change.

A region-of-interest masking technique was then applied to maximize the detection process in retaining only the portion of interest. This would involve the creation of a black-masked layer for peripheral areas, occluding from the view field of the camera and restricting it to work on the right side of the frame along the median road location. Such strategic masking would reduce most computational overheads beyond a large extent by avoiding unnecessary pedestrian detections outside a targeted area.

For the classification of pedestrian behavior, the detection system adopted a multi-line approach. Within a frame, there were five delineation lines, strategically located: three green and two red, designating non-jaywalking and jaywalking detection, respectively. Accordingly, this configuration enables subtle analyses of pedestrian trajectories and crossing patterns.

The default argument was initiated with the initialization of the YOLOv8 model, which detected pedestrians along with their bounding boxes. These were represented, for purposes of visualization, through purple rectangles added by OpenCV for real-time visualization. Now, the logic of pedestrian classification is explained below:

Every time a pedestrian's bounding box crossed the first green line, that person was classified as a non-jaywalker, and the respective counter incremented.

In case the bounding box of the same pedestrian intersected a red line later, the classification was updated to the jaywalker. The non-jaywalking counter was decremented to keep the statistics correct.

Now, by this tautological method, an exact tracing and classification of pedestrian behavior was possible, giving kinds of useful information that would allow inference on jaywalking patterns and frequencies in the surveyed area.

4.4 Distance Estimation

The most critical part of the study, however, would be the algorithm in the estimation of a pedestrian's distance. The estimation of the distance between the vehicle and a jaywalker would be calculated based on the dimension of pixels of the pedestrian detected through the model decision tree.

Euclidean Distance Method

It infers an estimate of the vehicle's distance from the detected pedestrian using the Euclidean distance. The method to compute the distance is relatively straightforward and very efficient. The steps are:

1. Obtain pixel coordinates of the pedestrian's bounding box and some reference point viewed on the vehicle; usually, it is the bottom center point of the image.

2. Computation of the bounding box: For this purpose, first, a bounding box shall be computed from the detection output of the YOLOv8 model for the pedestrian. The height and width of the pedestrian in terms of the dimensions of the image will then be estimated. The work used the diagonal length of the bounding box.

3. Center-point Calculation: The center-point of the pedestrian is determined by finding an average of the coordinates of the bounding box, which shall be used as a reference in calculating the distances.

4. The Euclidean distance formula is = $\sqrt{[(\boldsymbol{x2} - \boldsymbol{x1})^2 + (\boldsymbol{y2} - \boldsymbol{y1})^2]}$

Where (x1, y1) is a vehicle's reference point, and (x2, y2) are the coordinates of the center points of the pedestrian.

5. Pixel-to-Meter Conversion: The distance expressed in pixels is converted into meters by use of a predefined conversion factor. One can get it through known distances in the scene or obtain it from the specifications given by the camera.

6. Perspective Correction: This would be a perspective correction factor, depending on the angle and position of the camera. This is the correction of increasing distances estimated from the system by cubing to make them more accurate, especially when the distance from the camera is great.

4.5 Decision Tree Algorithm for Distance Prediction

Distance can be predicted based on pixel dimensions measured in images. The algorithm is useful for applications like ours in jaywalking detection. It involves the following steps:

Training the Model:

- **Dataset Preparation:** A decision tree model trained our dataset consisting of images with known distances; it had a total of 300 such images. The dataset was used to make the model robust enough to represent all kinds of scenarios and conditions. In this paper, the height factor and distance factor (Euclidean distance) are used for the estimation of the distance.
- **Model Learning:** It learns to map pixel dimensions or features onto the actual distances or targets during the training process. A decision tree learns by spotting patterns and trends in data.

Feature Selection:

- **Relevant Features:** The features include a Height Factor, which refers to the length of a bounding box, and a Distance Factor related to the Euclidean distance; these are driven by relevance and impact on estimating distances.
- **Feature Engineering:** Additional features can be engineered, based on the raw pixel dimension or derived to improve the performance of the model. These may include ratios, angles, or other transformations that are based on the original features.

Model Training:

- **Data Splitting:** It was divided into training, validation sets, and test sets. For training, approximately 210 images, which correspond to 70% of the dataset, were used. Approximately 45 images, which is 15% of the dataset, were used for validation, while another 15% of the dataset contained 45 images for a test set. The training set would be used in training the decision tree model, and the validation set would be used to evaluate its performance. Finally, this test set is used to test model performance.

- **Training Process:** The decision tree algorithm constructs a tree build where it involves every node corresponding to some features-based chosen decision. At any node, the model will recursively do a split on data to further minimize error in distance prediction. We have two phases for our train. Euclidean distance and the length of the diagonal of the bounding box were found in the training phase by feeding data from the training set into our jaywalk detection model. These two variables, with known real-life distances, are fed afterward in a decision tree algorithm model.
- **Validation:** The validation set will help check the accuracy and generalization of the model. This will also aid in tuning the parameters of the model since it prevents overfitting.

2. **Prediction:**
    - **Distance Estimation:** This decision tree model will be based on inputs of these distance and height factors for each detected jaywalker, predicting a distance. In this mechanism of prediction, what shall be done is to feed the distance factor and height factor into a trained model to obtain an estimated distance.
    - **Refinement:** These initial predictions shall undergo refinement, entailing masks or filters that clean out mistaken detections and add to the accuracy.
3. **Prediction Process:**
    - **Input to Model:** The factors on the distance and height of the detected jaywalker are fed into the trained decision tree model.
    - **Model Output:** It will process the inputs and output the predicted distance accordingly.
    - **Validation:** Since ground truth measurements are available, the distances which the model predicts are checked against real-life distances for accuracy. The accuracy rate reached around 87%.
4. **Error Correction:**
    - **Filtering:** Techniques that filter out inconsistent or mistaken predictions are applied. This might involve the removal of out-of-context predictions for the whole scene.
    - **Ensemble Methods:** With ensemble methods, different models—are those created in multiple decision trees or various algorithms—combined so that

prediction accuracy is improved. The final prediction of distance becomes the average or a weighted average of the predictions from the models.

5. **Model Prediction Results**:

   The model shows high predictive accuracy at shorter distances, with the best performance in the 2–5-meter range (0.349 error). Accuracy slightly decreases at 5-10 meters (0.4473 error) and drops significantly at 10-15 meters (0.864 error), indicating reduced precision for larger distances so Jaywalking distances above 10 meters were eliminated from the study.

Table 4.1: Model Performance Metrics for Pedestrian Distance Prediction

Metric	**Error**	**Mean Absolute Error (MAE)**	
Mean Absolute Error (MAE)	0.433509	1 - 2 meters	0.475
Mean Squared Error (MSE)	0.272516	2 - 5 meters	0.349
Root Mean Squared Error (RMSE)	0.52203	5 - 10 meters	0.447288136
R-Squared (R^2)	0.968708	10- 15 meters	0.864

This methodology gives a robust framework for estimating the distances in real-time video analysis by incorporating the decision tree algorithm with techniques such as error correction and ensemble methods. The method requires distance estimation to be pretty accurate for the detection and grading of jaywalking cases. On this note, the decision tree model can leverage informed decisions that create predictions associated with improving pedestrian safety and traffic management.

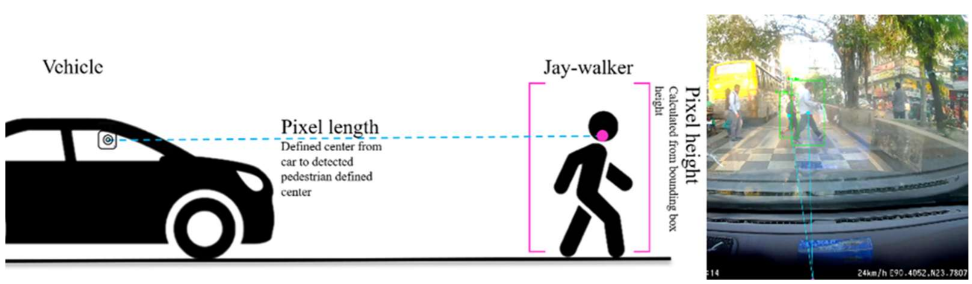


Fig. 4.1: Distance calculation of oncoming vehicles

4.6 Data Segmentation

Data segmentation was a critical step to categorize jaywalking incidents based on urban zones for detailed analysis. The process involved the following steps:

1. *Coordinate-Based Segmentation:* Using GPS coordinates, jaywalking incidents were segmented into residential, commercial, and industrial zones. This classification was aligned with the Detailed Area Plan (2022-2035) for the RAJUK Area to ensure geographic accuracy.

Zone Classification:

- **Residential Zones**: Areas mainly composed of housing and amenities for living, such as Mirpur, Bashundhara R/A, and Banani.
- **Commercial Zones**: Areas with high pedestrian and vehicular traffic due to commercial activities, such as Bangla-motor and Gulshan.
- **Industrial Zones**: Areas characterized by industrial activities and significant heavy vehicle movement, such as Gazipur and Tejgaon Industrial Area.

Jaywalk Identification

Pedestrian behavior in response to oncoming traffic was categorized into three types:

1. **No-Attempt (NA)**: The pedestrian does not attempt to jaywalk from the road median due to the perceived high risk from fast-moving or close-distance oncoming traffic.
2. **Semi-Commit (SC)**: The pedestrian attempts to jaywalk but does not fully commit to crossing, indicating hesitation due to marginally acceptable risk factors.
3. **Commit (C)**: The pedestrian fully commits to jaywalking, indicating low perceived risk due to slow vehicle speed or comfortable distance of oncoming traffic.

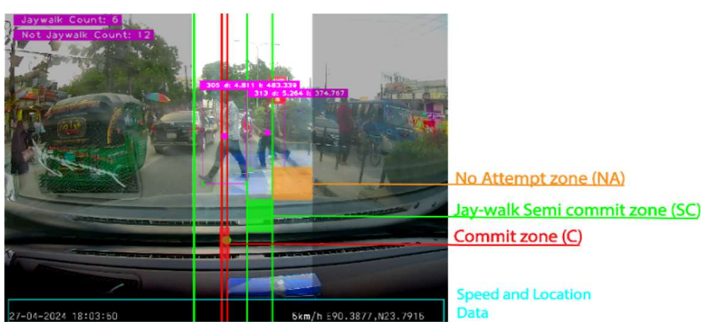


Fig 4.2: Identification category of jaywalking

Variables

The primary variables analyzed in this study were mean speeds and mean distances of oncoming traffic during jaywalking incidents. These variables were crucial in understanding the conditions under which pedestrians decide to jaywalk.

4.7 Statistical Analysis: Two-Sample t-tests

The statistical analysis involved comparing mean vehicle speeds and distances across different urban zones and times of the day to identify significant differences. The two-sample t-tests were employed for this purpose.

Objective: The objective of the two-sample t-tests was to determine if there are significant differences in vehicle speeds and pedestrian distances among residential, commercial, and industrial zones during weekdays and weekends.

Approach: The analysis was conducted as follows:

- **Hypotheses Formulation**:
    - Null Hypothesis (H_0): There is no significant difference between the means of the two groups.
    - Alternative Hypothesis (H_1): There is a significant difference between the means of the two groups.
    - **For average speed levels:**
    - $Ho = \mu 1 = \mu 2$
    - $H1 = \mu 1 \neq \mu 2$
    - **For average distance levels:**
    - $Ho = \mu 1 = \mu 2$
    - $H1 = \mu 1 \neq \mu 2$
    - **Where**:
    - $\mu 1$ is the mean speed or distance in Zone 1 (e.g., residential zone).
    - $\mu 2$ is the mean speed or distance in Zone 2 (e.g., commercial zone).

Group Comparisons: Two-sample t-tests were performed for both equal and unequal variances, comparing:

- Residential vs. Commercial Zones
- Residential vs. Industrial Zones
- Commercial vs. Industrial Zones

Time Comparisons: Comparisons were made for different times of the week (weekdays vs. weekends) to account for variations in traffic conditions.

Calculate the Test Statistic:

The T-test statistic for equal variances and unequal variances are given by:

$$\boldsymbol{t} = \frac{\overline{X1}-\overline{X2}}{\sqrt{Sp^2(\frac{1}{n1}+\frac{1}{n2})}} \quad (1) \qquad \boldsymbol{t} = \frac{\overline{X1}-\overline{X2}}{\sqrt{(\frac{1}{n1}+\frac{1}{n2})}} \quad (2)$$

Where:

- The t-test statistics for equal variance refers to Eq. (1) and t-test statistics for unequal variance refers to Eq. (2)
- $\overline{X1}$ *and* $\overline{X2}$ are the sample means of the two groups
- n1 and n2 are the sample sizes of the two groups.
- Sp^2 is the pooled variance, calculated as:

$$Sp^2 = \frac{(n1-1){S_1}^2-(n2-1){S_2}^2}{n1+n2-2}$$

Here, S1 and S2 are the sample variances of the two groups.

Degrees of Freedom: The degrees of freedom (df) for the test are given by:

Equal variance: **dғ=n1+n2−2**

Unequal variance: $$\text{dғ} = \frac{\left(\frac{{S_1}^2}{n1}+\frac{{S_2}^2}{n2}\right)^2}{\frac{\left(\frac{{S_1}^2}{n1}\right)^2}{n1+1}+\frac{\left(\frac{{S_2}^2}{n2}\right)^2}{n2+1}}$$

In this study, the significant differences were considered for P-value was less than 0.05.

Determine the Critical Value and P-value:

- The critical value for the T-test is obtained from the T-distribution table based on the degrees of freedom and the chosen significance level (α).

- The P-value is calculated to determine the probability of observing the test statistic under the null hypothesis.

1. **Critical Value and P-value**: The critical value for the t-test was obtained from the t-distribution table based on the degrees of freedom and the chosen significance level (α\alphaα). The P-value was calculated to determine the probability of observing the test statistic under the null hypothesis.
2. **Decision Rule**: If the calculated t-statistic was greater than the critical value or if the P-value was less than the significance level (α=0.05\alpha = 0.05α=0.05), the null hypothesis was rejected in favor of the alternative hypothesis, indicating a significant difference between the groups.

4.8 Validation and Reliability:

To ensure the reliability and validity of the data and analysis, several measures were taken.

Model Validation:

The YOLOv8 model was validated using a dataset containing known distances and speeds. This involved comparing the model's output with ground truth data to assess its accuracy.

Cross-validation techniques were employed to ensure the model's robustness. Data was split into training and validation sets multiple times to evaluate the model's performance and prevent overfitting.

4.9 Reliability Checks:

Repeated measures and consistency checks were conducted to confirm the reliability of the data. This included re-collecting and re-analyzing a subset of the data to verify consistency in results.

Statistical tests, such as calculating the intra-class correlation coefficient (ICC), were performed to assess the precision and accuracy of the measurements.

Ethical Considerations

Ethical considerations were addressed to ensure the privacy and consent of individuals involved in the study.

Informed Consent:

- Pedestrians were not individually identifiable in the recordings to ensure privacy. The data collection was designed to focus on the general behavior of pedestrians rather than on identifying individuals.
- Data collection was conducted in public spaces where individuals are typically not entitled to the same expectation of privacy as in private settings. Signs were posted in the data collection areas to inform the public of the ongoing research.

Data Security:

- All collected data was stored securely with access restricted to authorized personnel only. Data encryption was used to protect sensitive information during storage and transmission.
- Anonymization techniques were applied to the data to remove any identifying information, ensuring the privacy of individuals was maintained throughout the study.

Limitations of the Study

Acknowledge any limitations that might affect the study's findings or generalizability.

Geographical Limitations:

- The study is limited to specific zones in Dhaka and may not be generalizable to other urban areas without similar conditions. Differences in urban infrastructure, population density, and traffic patterns may influence the applicability of the findings to other cities.

Temporal Limitations:

- Data was collected over a specific period and may not account for seasonal variations or long-term trends. For example, pedestrian and traffic behaviors might change during different seasons, festivals, or holidays, which were not captured in this study.

Technical Limitations:

- The accuracy of distance and speed estimations may be influenced by the quality of the dashcam footage and GPS data. Factors such as lighting conditions, camera resolution, and GPS signal strength can affect the precision of the measurements.

- The YOLOv8 model, while advanced, may still have limitations in detecting and tracking pedestrians under certain conditions, such as in very crowded or low-visibility scenarios.

Experimental Goals:

By conducting this detailed statistical analysis, the study aimed to achieve the following:

1. **Understand Zone-Specific Behavior**: Identify how pedestrian jaywalking behavior varies across residential, commercial, and industrial zones. This helps in understanding the influence of different urban settings on jaywalking behavior.
2. **Analyze Time-Specific Variations**: Examine how jaywalking incidents vary between peak and off-peak hours on weekdays and weekends. This helps in understanding temporal variations in jaywalking behavior.
3. **Inform Policy and Urban Planning**: Provide actionable insights for urban planners and policymakers to develop targeted interventions for improving pedestrian safety. This includes recommendations for the placement of road crossings, speed limitations, and modifications to traffic signal timings.
4. **Develop Predictive Models**: Use the findings to inform the development of predictive models for jaywalking behavior, enhancing the ability to simulate traffic patterns and improve pedestrian safety in urban areas.

The methodology employed in this study involved a comprehensive approach to segmenting and analyzing jaywalking data based on urban zones and traffic conditions. By leveraging advanced image processing techniques and robust statistical analysis, the study aimed to uncover significant insights into pedestrian behavior and traffic safety in Dhaka, Bangladesh. The findings from this analysis provide valuable information for urban planners and policymakers to develop targeted interventions for improving pedestrian safety and managing urban traffic effectively.

Limitations of the Methodology

Regardless of the fact that the methodology was broad and all-embracing, some shortcomings were also noted.

1. Geographical Coverage: The research was restricted to the city of Dhaka hence the results could not be generalized to other cities.

2. Seasonal Influence: The period of collection of data was limited to six months which could have eliminated some seasons of pedestrian activity.

3. Modelling Limitations: The model YOLOv8 could not recognize above 10 meters and in very congested areas for instance people crossing the street without the traffic light.

4. Inclusion Criteria: Meters More than 10 meters from the nearest mobile object (vehicular) crossing were not included because of lower detection accuracy.

CHAPTER FIVE: ANALYSIS AND INTERPRETATION

The goal of this research was to determine the average traffic speed and the average distance of jaywalkers from oncoming traffic during jaywalks in three zones (Residential, Industrial, Commercial) in Dhaka at different times of the day. Using t-tests, we compared the average traffic speed and the average distance of jaywalkers from oncoming traffic during jaywalks across these zones. Both equal and unequal variances were considered during the t-tests, and we used a 95% confidence level. Differences in average speed and distance between the zones were regarded as statistically significant if the p-value was less than 0.05.

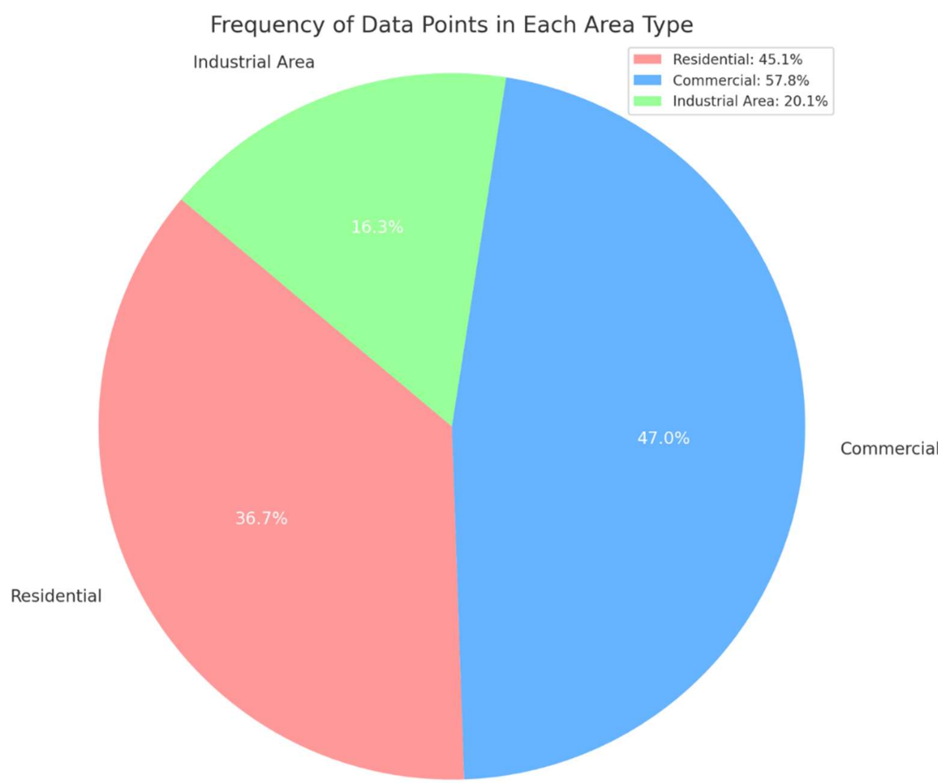


Fig. 5.1: % of data collected in each zone for a specified time

The pie chart provides a visual representation of the distribution of data points collected from different area types (Residential, Commercial, and Industrial) in our research on jaywalking behaviour and traffic conditions. The distribution of data points across different area types provides valuable insights into the prevalence of jaywalking incidents and traffic interactions in these zones. The higher frequency of data in commercial and residential zones suggests that these areas require focused attention for improving pedestrian safety and traffic management. Industrial zones, despite having fewer data points, also exhibit significant jaywalking behaviour, necessitating targeted interventions.

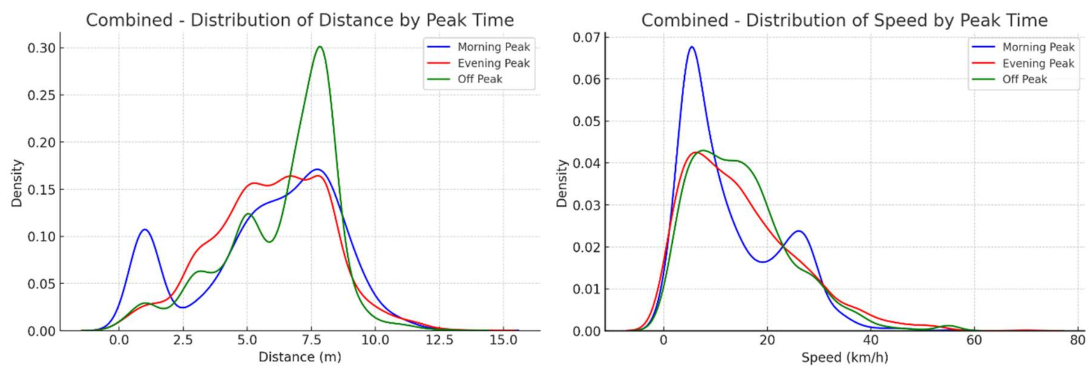


Fig. 5.2: KDE plots of jaywalkers' density versus oncoming traffic speeds and distance at various peak times.

After analysing the combined data of all the zones, KDE plots [Fig. 5.2] revealed two distinct clusters of frequently travelled distances during the morning peak: shorter distances (around 1 meter) and longer distances (around 7.5 meters). The closer jaywalking distance could be attributed to rush hour in the office and educational institution, while the longer distance could be due to people exercising more caution. The evening peak showed a more even distribution between shorter and longer distances, where the most prominent peak is around 8 meters and another smaller secondary peak around 3-4 meters. This indicates mixed behaviour, with most crossing at safer distances but some still taking risks, perhaps influenced by residual workday stress or fatigue. The off-peak revealed a peak of around 7.5

meters, indicating longer-distance jaywalking initiation likely due to higher vehicle speeds during off-peak hours, prompting pedestrians to cross from safety.

For speed, during the morning peak, it was concentrated around 10 km/h, suggesting slower-moving traffic, presumably due to the rush hour as people commute to work. In contrast, during off-peak hours, the distribution showed a broader spread, with a noticeable peak around 15-20 km/h, indicating fewer vehicles and less congestion, allowing for higher speeds, prompting pedestrians to assess their surroundings before crossing [39], and this is similar for the evening peak, which lies between these two, with jaywalking frequency decreasing from lower speed to higher speed, indicating inherent lower risk-taking behaviour.

Table 5.1: Comparison of mean traffic speed by time of day and zone

Variable	Time	Comparison	Mean	P-Value for Equal /Unequal Variance
Vehicle Speed (km/h)	Weekday	Residential/Commercial	13.48 / 11.47	0.001/0.001*
		Residential/Industrial	13.48 / 16.95	0.001/0.001*
		Commercial/Industrial	11.47 / 16.95	0.001/0.001*
	Weekend	Residential/Commercial	16.41 / 10.77	0.001/0.001*
		Residential/Industrial	16.41 / 11.25	0.001/0.001*

Variable	Time	Comparison	Mean	P-Value for Equal /Unequal Variance
		Commercial/Industrial	10.77 / 11.25	0.240/0.241
Vehicle Distance (m)	Weekday	Residential/Commercial	7.15 / 5.32	0.001/0.001*
		Residential/Industrial	7.15 / 6.15	0.001/0.001*
		Commercial/Industrial	5.32 / 6.15	0.020/0.030*
	Weekend	Residential/Commercial	6.86 / 4.94	0.001/0.001*
		Residential/Industrial	6.86 / 7.55	0.001/0.001*
		Commercial/Industrial	4.94 / 7.55	0.001/0.001*

*Significant differences at 5% significance level ($p < 0.05$).

During weekdays, the average approach speeds of the closest vehicle at jaywalking initiation vary significantly across urban zones: industrial zones average 16.95 km/h, residential zones 13.48 km/h, and commercial zones 11.47 km/h. On weekends, speeds also vary, with residential zones averaging 16.41 km/h, commercial zones 10.77 km/h, and industrial zones 11.25 km/h. The higher speeds in industrial zones during weekdays can be attributed to the active operations of factories, warehouses, and businesses, which necessitate faster vehicle movement to meet schedules and maintain productivity. This trend is also observed in commercial zones. Conversely, during weekends, residential zones see less pedestrian traffic as people are not commuting to work or school, potentially leading to higher driving speeds compared to the reduced speeds in industrial zones.

Jaywalking initiation distances from the closest oncoming vehicle vary by zone, averaging 7.15 meters in residential zones, 6.15 meters in industrial zones, and 5.32 meters in commercial zones. On weekends, these distances are 6.86 meters in residential zones, 7.55 meters in industrial zones, and 4.94 meters in commercial zones. These variations in jaywalking distances can be attributed to the approach speeds in each zone. The higher mean speed in industrial zones on weekdays, compared to residential zones, may explain the greater jaywalking distances in industrial zones during weekdays. Pedestrians in these zones might cross from farther away for safety due to the higher speeds and heavy traffic. Perhaps the surrounding characteristics of each zone can be a cause. This pattern is also seen in commercial zones, indicating that jaywalking behavior varies based on the zone. It was observed in a study that pedestrians' movement in road crossing was heavily affected by its surrounding environment [39].

Table 5.2: Comparison of mean speed of nearest oncoming vehicles by time of day and Zone.

Urban Zone	Comparison	Weekday		Weekend	
		Mean Vehicle Speed (km/h)	**P-Value for Equal/ Unequal Variance**	**Mean Vehicle Speed (km/h)**	**P-Value for Equal /Unequal Variance**
Residential	Morning/Off-Peak	5.02 / 18.00	0.162 / 0.084	26.18 / 15.04	0.001 / 0.001*
	Evening/Off-Peak	16.18 / 18.00	0.834 / 0.762	9.31 / 15.04	0.001 / 0.001*
	Morning/Evening	5.02 / 16.18	0.342 / 0.002	26.18 / 9.31	0.001 / 0.001*
Commercial	Morning/Off-Peak	10.60 / 12.86	0.021 / 0.023*	6.68 / 8.41	0.620 / 0.551

	Evening/Off-Peak	14.99 / 12.86	0.032 / 0.061	17.31 / 8.41	0.054 / 0.520
	Morning/Evening	10.60 / 14.99	0.001 / 0.001*	6.68 / 17.31	0.410 / 0.572
Industrial	Morning/Off-Peak	8.08 / 16.41	0.001 / 0.001*	8.49 / 17.59	0.001 / 0.001*
	Evening/Off-Peak	12.79 / 16.41	0.001 / 0.001*	17.21 / 17.59	0.844 / 0.821
	Morning/Evening	8.08 / 12.79	0.001 / 0.001*	8.49 / 17.21	0.001 / 0.001*

*Significant differences at 5% significance level ($p < 0.05$)

Table 5.3: Comparison of time on mean vehicle distance of approaching vehicle among different zones

Category	**Comparison**	**Weekday**		**Weekend**	
		Mean Vehicle Distance (m)	**P-Value for Equal / Unequal Variance**	**Mean Vehicle Distance (m)**	**P-Value for Equal /Unequal Variance**
Residential	Morning/Off-Peak	0.99 / 7.48	0.624 / 0.741	8.05 / 7.41	0.001 / 0.001*
	Evening/Off-Peak	6.78 / 7.48	0.001 / 0.001*	5.38 / 7.41	0.001 / 0.001*
	Morning/Evening	0.99 / 6.78	0.001 / 0.001*	8.05 / 5.38	0.001 / 0.001*

Commercial	Morning/Off-Peak	6.57 / 6.32	0.064 / 0.062	5.68 / 4.28	0.001 / 0.001*
	Evening/Off-Peak	6.30 / 6.32	0.855 / 0.854	4.88 / 4.28	0.001 / 0.002*
	Morning/Evening	6.57 / 6.30	0.052 / 0.052	5.68 / 4.88	0.001 / 0.001*
Industrial	Morning/Off-Peak	6.13 / 6.24	0.624 / 0.571	7.22 / 6.39	0.001 / 0.001*
	Evening/Off-Peak	6.05 / 6.24	0.561 / 0.557	6.13 / 6.39	0.133 / 0.124
	Morning/Evening	6.13 / 6.05	0.802 / 0.776	7.22 / 6.13	0.001 / 0.001*

*Significant differences at 5% significance level ($p < 0.05$)

In residential zones during weekdays, oncoming traffic speeds show distinct variations in jaywalking behavior. In the morning, average speeds are 5.02 km/h, with pedestrians initiating jaywalking from an average distance of 0.99 meters. The lower speeds may make pedestrians feel more comfortable crossing from a closer distance. In contrast, during off-peak hours, speeds increase to 18.00 km/h, and jaywalking distances extend to 7.48 meters. This increase in distance may be due to the need to cross from farther away for safety because of the higher vehicle speeds in lower traffic. In the evening, speeds average 16.18 km/h, and jaywalkers start from 6.78 meters away. This may be because there are fewer vehicles compared to the morning, but more than during off-peak hours, leading to slightly shorter jaywalking distances than those observed during off-peak times.

On weekends, morning speeds average 25.93 km/h with a crossing distance of 8.05 meters, likely due to the reduced morning rush allowing for higher speeds. In the evening, speeds drop to 8.06 km/h with a shorter crossing distance of 5.38 meters, possibly because recreational activities during weekends increase traffic volume and slow down traffic. During off-peak hours, speeds average 14.31 km/h with a crossing distance of 7.41 meters, as lower traffic volumes may permit higher speeds. An outcome from a study similarly showed that in the morning large group of pedestrians during crossing accepted longer gaps compared to individuals [40].

In commercial zones, weekday speeds remain relatively stable. Morning speeds average 10.60 km/h, while evening speeds average 14.99 km/h. The increase in evening speed can be attributed to the reduction in commuter traffic and errands in the morning, which creates a less congested environment and allows for higher speeds. Perhaps, during the morning rush drivers often proceed cautiously due to increased activity and perceived urgency, leading to slower speeds. As the day progresses and this activity diminishes, drivers experience less pressure and greater ease, resulting in faster speeds. During off-peak hours, speeds average 12.86 km/h, slightly lower than in the evening. This reduction can be attributed to the presence of varied traffic types, such as delivery vehicles and service traffic, which contribute to a more complex driving environment and prompt drivers to reduce their speed for safety and efficiency.

On weekends, in the morning, speeds average 7.20 km/h with a crossing distance of 5.68 meters. This may be because, without the rush of weekdays, people are more cautious about safety and choose to cross from farther away and may be people tend to cross from farther distance when there are larger group of people instead of being alone [40]. During off-peak hours, speeds are lower at 6.25 km/h and crossing distances average of 4.28 meters possibly as people feel comfortable crossing from shorter distances when speeds are lower. In the evening, speeds rise to 13.67 km/h with crossing distances averaging 4.88 meters, indicating that people may accept increased risk despite higher speeds.

In industrial zones during weekdays, traffic speeds vary significantly. In the morning, average speeds are 8.08 km/h, likely due to high vehicle volumes as industrial activities commence, leading to slower traffic. This contrasts with off-peak hours, where speeds rise to 16.41 km/h, as fewer vehicles on the road allow for faster movement. In the evening, speeds average 12.79 km/h, possibly due to reduced traffic from fewer deliveries and operational activities compared to the morning, but still higher than during off-peak hours. The higher risk-taking behavior of pedestrians in industrial zones can be attributed to the limited availability of crossing facilities. A study by Pasha et al. [41] found that different locations in Dhaka exhibited varying levels of crossing facility usage, supporting the claim that jaywalking characteristics change based on the zone. Additionally, another study found a strong correlation between pedestrians' mid-block crossing behavior and traffic speed [42]. On weekends, pedestrian behavior changes notably, with morning speeds averaging 8.49 km/h and crossing distances of 7.22 meters, possibly due to residual traffic and increased local activity. Although speeds are lower, people may prefer to cross from farther away as they are not in a rush during weekends. In contrast, during off-peak hours, speeds average 17.59 km/h with a shorter crossing distance of 6.39 meters, indicating higher risk tolerance and increased speeds. In the evening, speeds average 17.21 km/h with a crossing distance of 6.13 meters, reflecting behavior similar to off-peak hours.

Conclusion

The analysis reveals significant variability in jaywalking behaviour across different urban zones and times of the day/week. Residential zones show significant differences in both speeds and distances at different times, while commercial and industrial zones exhibit more consistent behaviour. These insights highlight the need for targeted traffic management strategies to enhance pedestrian safety and compliance with traffic laws.

By understanding these dynamics, urban planners and traffic managers can implement more effective measures to mitigate jaywalking risks and ensure safer pedestrian environments in different zones.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

Introduction

This chapter summarizes the findings of the study, provides recommendations based on the results, addresses the limitations encountered during the research, and suggests directions for future studies. The study's primary goal was to understand how the distance and speed of oncoming traffic influence jaywalking behavior in various urban zones in Dhaka, Bangladesh, and to propose measures to enhance pedestrian safety.

Conclusions

The research revealed significant insights into pedestrian jaywalking behavior in different urban zones. Key findings include:

1. **Zone-Specific Jaywalking Behaviour:** Pedestrians in commercial zones tend to initiate jaywalking at closer distances to oncoming traffic compared to those in residential and industrial zones. This behaviour is influenced by the higher pedestrian activity and mixed-use characteristics of commercial areas.
2. **Time-Specific Variations:** Jaywalking incidents are more frequent during peak hours in commercial zones, while residential zones see more jaywalking during off-peak hours. This highlights the need for time-specific interventions.
3. **Impact of Traffic Speed and Distance:** There is a noticeable difference in acceptable traffic speed and perceived distance during jaywalking across different zones and times. Pedestrians tend to jaywalk when they perceive oncoming traffic as slow or distant enough to safely cross.
4. **Predictive Model Development:** The study successfully developed predictive models for jaywalking behavior using advanced image processing techniques and statistical analysis, providing a robust framework for future traffic safety research.

Recommendations

Based on the study's findings and a review of related research, the following recommendations are proposed to enhance pedestrian safety and manage jaywalking behavior effectively:

1. **Enhanced Pedestrian Infrastructure:**
    - Install pedestrian overpasses and underpasses in high-traffic commercial zones.
    - Implement wider sidewalks and more crosswalks with clear markings.
    - Introduce pedestrian signals at key intersections to control jaywalking.

2. **Traffic Calming Measures:**
    - Reduce speed limits in areas with high pedestrian activity, especially during peak hours.
    - Implement traffic calming devices such as speed humps and raised crosswalks in residential zones.

3. **Public Awareness Campaigns:**
    - Conduct awareness campaigns to educate pedestrians about the dangers of jaywalking and promote the use of designated crossing areas.
    - Use behavioral change models to design effective communication strategies and educational materials.

4. **Law Enforcement and Policy:**
    - Increase the enforcement of existing traffic laws related to pedestrian safety and jaywalking.
    - Implement stricter penalties for violations to deter jaywalking.
    - Develop policies that prioritize pedestrian safety in urban planning and traffic management.

5. **Technological Interventions:**
    - Deploy advanced surveillance systems with real-time jaywalking detection capabilities.
    - Utilize data from predictive models to inform dynamic traffic signal adjustments and pedestrian crossing timings.

Limitations and Future Research

The study encountered several limitations that should be addressed in future research:

1. **Limited Dashcam Coverage:**
   - The dashcam setup only captured the right side of the lane, potentially missing jaywalking incidents on the left side. Future studies should use multiple dashcams to provide a comprehensive view of all lanes.
2. **Distance Detection Limitation:**
   - The dashcam was unable to accurately detect distances beyond 10 meters. This limitation can be addressed by using higher resolution cameras or supplementary distance measurement technologies like LiDAR.
3. **Data Collection Constraints:**
   - Data was collected over a limited period, which may not account for seasonal variations or long-term trends in jaywalking behavior. Future studies should include extended data collection periods to capture these variations.
4. **Urban Zone Variability:**
   - The study focused on specific zones in Dhaka, which may not be generalizable to other urban areas with different characteristics. Expanding the study to include multiple cities with diverse urban layouts would enhance the generalizability of the findings.
5. **Behavioural Factors:**
   - While the study focused on the influence of traffic speed and distance, other behavioral factors such as pedestrian demographics, purpose of travel, and environmental conditions were not extensively analyzed. Future research

should incorporate these factors to provide a more holistic understanding of jaywalking behavior.

By addressing these limitations and incorporating the proposed improvements, future research can build on the findings of this study to develop more effective strategies for enhancing pedestrian safety and managing jaywalking behavior in urban environments.

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