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Tint Detection Using Image Analysis

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Abstract
This paper introduces an automated Tint Detection System designed to meet regulatory requirements for vehicle window tinting through advanced image analysis techniques. Excessive tinting on vehicle windows can impair visibility, affecting road safety and law enforcement's ability to monitor vehicles. Traditional manual inspections are time-intensive, costly, and prone to error. This project proposes a system that automates tint detection in real-time using a modular pipeline incorporating YOLOv5 for vehicle detection, U-Net for window segmentation, and a Convolutional Neural Network (CNN) for Visual Light Transmission (VLT) analysis. Our system facilitates efficient, automated detection of tint levels, supporting law enforcement in ensuring compliance with minimal manual intervention.
Keywords: *Image Analysis, Tint Detection, YOLO, U-Net, Convolutional Neural Network, Real-Time Processing, Vehicle Compliance.*

1. Introduction

In modern automotive systems, glass windows are integral to vehicle design, playing a vital role in ensuring visibility, safety, and comfort for both drivers and passengers. The windshield at the front of a vehicle provides a clear, unobstructed view of the road ahead, enabling the driver to adjust speed, navigate safely, and respond to changing traffic conditions. This visibility is crucial for accident prevention, as it allows drivers to make quick decisions based on road conditions, potential obstacles, and the actions of other vehicles. Similarly, rear and side windows offer critical visibility to other vehicles and the surrounding environment, enhancing informed driving decisions and overall situational awareness. For passengers, side windows offer a view of the outside world, contributing to comfort and situational awareness, and they can also serve as emergency exits, adding an important layer of safety in critical situations. Furthermore, mirrors positioned inside vehicles, particularly those near the driver's seat, significantly enhance safety by enabling the driver to monitor approaching vehicles and make timely decisions to prevent accidents. These combined elements work together to create a safer driving experience. Beyond ensuring the comfort and safety of vehicle occupants, the transparency of automotive windows plays a critical role in public safety. Law enforcement agencies rely on the ability to see through vehicle windows to monitor occupants, particularly in scenarios involving suspicious activities or accidents. Visibility through windows allows officers to assess potential threats, detect illegal activities, and identify individuals who may be involved in criminal behavior. In emergency situations, quick visual access to the vehicle's interior can aid in faster decision-making and enhance response times, ultimately helping to reduce crime and ensure community safety. However, the widespread use of aftermarket tinting films has complicated this process. Tinting films, which are often purchased from the grey market, can significantly reduce the visibility of a vehicle's interior from the outside. While some degree of window tinting can provide privacy, reduce glare, and improve comfort, excessive tinting poses challenges for law enforcement, making it difficult to monitor the occupants or assess potential risks within a vehicle. Excessively tinted windows can hinder law enforcement's ability to identify individuals during critical investigations, impacting efforts to maintain public safety and compliance with legal standards. In response to these issues, many countries and states have established stringent regulations specifying acceptable levels of Visual Light Transmission (VLT) and Visual Light Reflectance (VLR) for vehicle windows. VLT, which represents the percentage of light allowed through the window, is particularly crucial as it directly affects visibility. High levels of tint reduce VLT, making it harder for law enforcement to see inside the vehicle and assess its occupants. While these regulations vary from region to region, their common purpose is to ensure a balanced approach between privacy and public safety. Despite regulatory efforts, violations are common. In many regions, vehicles exceed the legal limits of tinting, often due to inadequate monitoring and enforcement mechanisms. Traditional enforcement methods, which rely heavily on manual inspections by law enforcement officers using handheld VLT meters, are time-consuming, labor-intensive, and challenging to implement consistently. This manual approach is especially impractical in high-traffic areas or densely populated urban settings, where high vehicle volumes make comprehensive inspection nearly impossible. Consequently, a significant number of vehicles with illegal tint levels go undetected, leading to ongoing challenges in maintaining road safety and regulatory compliance. This project addresses these challenges by proposing the development of a video-based automatic tint detection system. The system is designed to assess the VLT levels of vehicle windows and identify vehicles that exceed legal tinting limits, facilitating a more efficient, scalable, and consistent approach to tint regulation enforcement. Leveraging advanced image analysis techniques, the system uses deep learning models to detect vehicles, segment window areas, and evaluate tint levels in real time. This automated process allows for continuous monitoring without requiring constant human intervention, thereby enhancing efficiency and coverage. By addressing these issues through automation, this project aims to enhance road safety, support law enforcement efforts, and contribute to the broader trend of developing smart urban infrastructures. The proposed tint detection system not only aligns with current legal standards for vehicle window tinting but also offers a scalable, efficient solution that can be adapted for future expansions, such as integration with broader smart city initiatives, data-sharing frameworks, and real-time compliance reporting [1].

2. Literature Review

The YOLO (You Only Look Once) model has become a cornerstone in vehicle detection and classification due to its high efficiency and speed in real-time object detection tasks. Permana and Lestiawan (2024) demonstrated the practicality of YOLO in tracking and classifying multiple vehicle types—such as cars, motorcycles, trucks, and buses—in an urban setting. Their study, conducted in Tangerang City, Indonesia, reported an impressive accuracy of 79% when YOLO was used for vehicle detection in varied traffic environments, underscoring its capability to adapt to complex real-world conditions. In another study, Bathija (2019) paired YOLO with the SORT tracking algorithm to enhance multi-object tracking in urban traffic systems, utilizing a dataset comprising 800 images across six classes, and achieving precise vehicle and pedestrian detection, showing the potential for improving tracking accuracy through robust algorithmic combinations. Mohana et al. (2022) explored YOLOv3's integration with edge computing to address the limitations associated with centralized cloud computing in real-time applications. By processing data locally, this approach drastically reduces latency, enabling faster responses in critical urban mobility scenarios. Mohana et al. leveraged YOLOv3's high accuracy in real-time applications, particularly in dense traffic zones, where rapid adaptation to changing traffic patterns is essential. The deployment of edge devices for processing also minimized data transmission costs, highlighting a cost-effective and efficient solution for real-time traffic monitoring. Beyond simple vehicle detection, studies have shown the advantages of pairing YOLO with other filtering methods for enhanced accuracy. Asha et al. (2018) implemented YOLO alongside correlation filters for vehicle counting, which provided greater stability in object tracking and 7 improved performance across various traffic conditions. This combination, however, faced challenges in processing time and lane adaptation, as the method was optimized for

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single-lane environments. To address such limitations, Xia et al. (2016) integrated YOLO with Gaussian mixture models and virtual loop algorithms to improve object detection and tracking, even under occlusion and other challenging environmental factors. Their approach yielded an impressive 98% detection accuracy, suggesting that integrating YOLO with supplementary models can significantly enhance performance in high-density, multi-lane traffic environments. The need to detect and analyze vehicle attributes beyond general classification has led to the use of Convolutional Neural Networks (CNNs) for windshield tint detection, adding an additional layer of functionality to vehicle monitoring systems. Kaliyaperumal (2024) presented a CNN-based approach that detects windshield tint levels using IoT and image processing techniques, including contour and histogram analysis, enabling the identification of vehicles with illegal tinting while they remain in motion. This approach not only aids law enforcement but also avoids the disruption of traffic flow, making it practical for real-time traffic management scenarios. Additionally, in a study conducted by Gomaa et al. (2019), CNN was effectively integrated with optical flow for real-time traffic data analysis, proving CNN's robustness in dynamically assessing vehicle attributes while handling large traffic volumes. In addressing implementation challenges, Galletta et al. (2020) demonstrated the use of Functionas-a-Service (FaaS) on edge devices to support scalable and adaptive traffic monitoring systems. This edge-computing paradigm provides local processing capability that reduces latency and optimizes resource use, allowing for efficient real-time monitoring. Their study emphasized the high precision of the YOLO model deployed in conjunction with edge computing (up to 95%) across multiple traffic monitoring stations, showcasing the benefits of distributed processing in smart urban environments. Studies have also highlighted the broader implications of YOLO and CNN-based systems for urban mobility enhancement. For example, Aliane et al. (2020) explored the application of AI for criminal offense detection within vehicles, using onboard cameras and YOLO-based traffic sign identification systems to automatically alert drivers of traffic violations. This smart in-vehicle system serves as a model for comprehensive traffic rule enforcement, which could be expanded to include vehicle attributes like tint level and vehicle type identification. These findings collectively indicate that combining YOLO with supplementary models, such as 8 CNN and edge computing, offers a multi-dimensional approach to urban traffic monitoring [2-5]. The integration of deep learning techniques not only enhances detection capabilities but also enables systems to monitor compliance with regulations (e.g., tint detection) and respond swiftly to traffic flow changes. Thus, these models support both operational efficiency in real-time urban traffic monitoring and regulatory compliance, promoting safer and more sustainable urban mobility, shown in Figure 1.

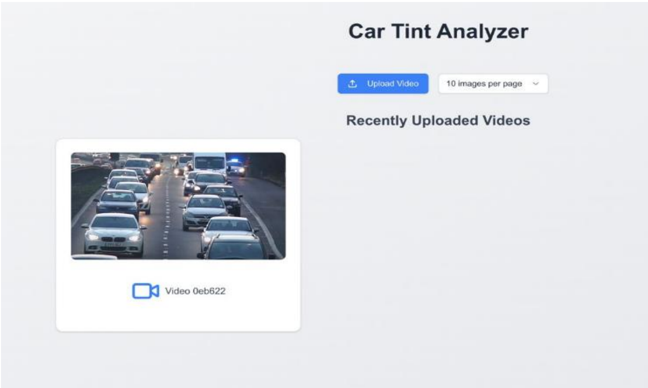

Figure 1 Live Stream of Traffic

3. Methodology

The Tint Detection System utilizes a modular design to ensure that each stage of the pipeline contributes to accurate, efficient, and real-time analysis. By leveraging deep learning models for vehicle detection, window segmentation, and tint level classification, the system performs automated tint compliance monitoring in diverse traffic and environmental conditions [6-9]. Below is a detailed breakdown of each module within the system.

3.1. Vehicle Detection

Vehicle detection is the initial stage in the tint detection process, where the system identifies vehicles within live video feeds. We employ YOLOv5 (You Only Look Once, version 5), a state-

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of-the-art object detection model known for its high speed and accuracy in real-time applications. YOLOv5 uses a single-stage convolutional neural network architecture to detect objects within an image, processing video frames individually to ensure seamless, high-speed detection. The YOLOv5 model is specifically optimized for high-traffic environments, where multiple vehicles may appear in a single frame. Each detected vehicle is isolated by a bounding box, which provides precise spatial coordinates of the vehicle within the frame. This bounding box allows for targeted window segmentation, directing subsequent stages to focus only on areas within the vehicle. YOLOv5's architecture enables it to differentiate between vehicle types (e.g., cars, trucks, buses) and quickly identify vehicles across various viewing angles. This versatility is essential for effective deployment in urban areas, where vehicles may appear from multiple directions and under varied lighting conditions [10-13]. To further enhance accuracy and efficiency, the YOLOv5 model is fine-tuned with a custom dataset that includes vehicles with different tint levels and environmental backgrounds. This fine-tuning step improves the model's robustness in detecting vehicles in diverse lighting conditions, weather, and high-density traffic scenarios, ensuring reliable detection performance even during peak traffic hours, shown in Figure 2 [14-15].

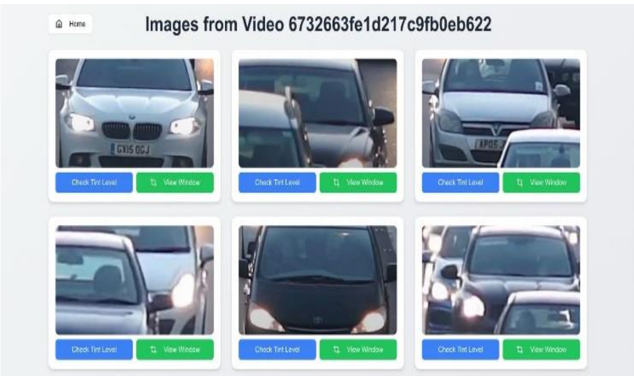

Figure 2 Detection of Cars from Live Stream using YOLOv5

3.2. Window Segmentation

Once a vehicle is detected, the system moves to the window segmentation stage, where it isolates window regions within the bounding box. We use the U-Net model for this task, a convolutional neural network architecture specifically designed for image segmentation tasks that require precision along object edges. U-Net's encoder-decoder structure with skip connections allows it to capture fine details while maintaining contextual information, making it ideal for segmenting windows from complex backgrounds, including reflections and adjacent vehicle parts. The U-Net model operates by creating a binary mask over each detected vehicle image, where pixels corresponding to window regions are marked, and other regions (e.g., vehicle body, wheels) are excluded. The skip connections in U-Net enable high-precision segmentation at the pixel level, allowing it to identify various types of windows—front, side, and rear—accurately across different vehicle models. By focusing solely on window areas, this module ensures that only relevant portions of the vehicle are analyzed for tint levels, thereby improving the overall accuracy of the system. To further enhance segmentation precision, U-Net is trained on an annotated dataset containing various vehicle window shapes, angles, and tint levels. The dataset also includes images captured under different lighting conditions, such as daylight, dusk, and artificial lighting, ensuring that U-Net can perform accurately in diverse settings. This adaptability is crucial for maintaining segmentation accuracy in real-world deployment, where lighting variations and environmental conditions are unpredictable, shown in Figure 3.

Figure 3 Cropped Window Segment

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3.3. Tint Level Classification

With the window areas segmented, the system proceeds to the tint level classification stage. Here, a Convolutional Neural Network (CNN) classifier evaluates the Visual Light Transmission (VLT) levels of the segmented windows, categorizing them as legal or illegal based on predefined regulatory standards. The CNN model is designed to analyze variations in light transmission by processing pixel intensity and color data, allowing it to estimate the VLT percentage. The CNN classifier is trained using a labeled dataset of window images with known VLT values, captured under various lighting and weather conditions. This dataset includes both legally compliant and non-compliant tints, enabling CNN to learn the nuances of legal and illegal tint levels accurately. The model is fine-tuned to perform consistently across different scenarios, including nighttime settings, overcast days, and direct sunlight, which may otherwise impact the accuracy of VLT analysis, shown in Figure 4.

Figure 4 Tint Level Detection

To address potential inaccuracies due to environmental conditions, the CNN model employs data augmentation techniques, such as brightness adjustment and contrast variation, to simulate different lighting effects. This approach helps the model generalize to real-world conditions, where changes in ambient lighting could otherwise hinder classification accuracy. The system can thus maintain high accuracy in distinguishing between compliant and non-compliant tint levels, supporting reliable, regulatory-grade assessment.

3.4. Data Logging and Compliance Reporting

Upon detecting a violation, the system automatically logs relevant data to a MongoDB database, facilitating comprehensive compliance tracking and reporting. This database stores essential information for each detected violation, including vehicle license plate data, timestamp, location, and VLT classification result. MongoDB's NoSQL architecture is chosen for its flexibility, scalability, and ability to handle large volumes of unstructured data, making it ideal for high-traffic environments.

The database structure supports both real-time and historical data access, allowing law enforcement agencies to query the system for specific violations, analyze trends over time, and generate compliance reports. This logging system enables long-term tracking of violations and repeat offenders, providing valuable insights into compliance rates and helping authorities optimize enforcement strategies. Furthermore, MongoDB's compatibility with cloud-based systems and IoT frameworks facilitates integration with broader smart city infrastructures. This integration allows for centralized data collection and sharing across multiple monitoring locations, enabling a unified approach to tint regulation enforcement across different urban areas. The database also supports compliance reporting by generating detailed statistics on detected violations, geographic distribution, and time-based trends, empowering law enforcement to make data-driven decisions and ensure consistent enforcement of tint regulations. The MongoDB database also supports comprehensive reporting functionality, enabling the generation of detailed compliance reports that summarize violation data across monitored areas. This data provides insights into compliance rates, high-risk locations, and time-based trends. The reporting module facilitates resource allocation for enforcement, targeted interventions in high-violation areas, and data-driven policy improvements, enhancing transparency and accountability for regulatory authorities.

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3.5. System Architecture

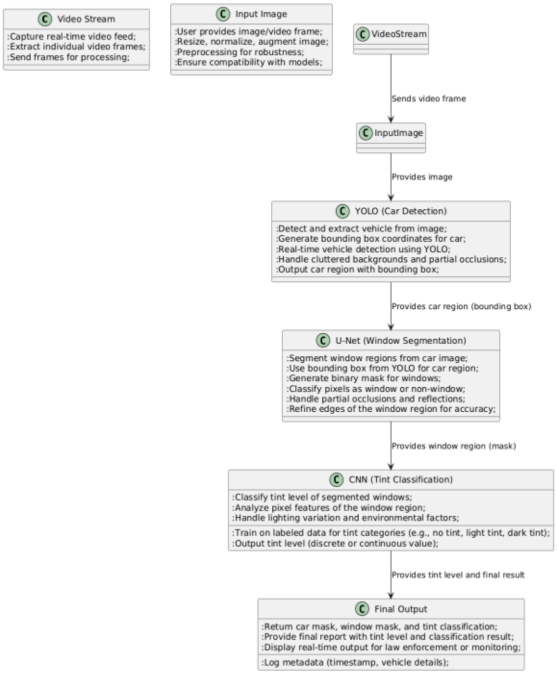

Figure 5 System Architecture Diagram

The system architecture for vehicle window tint detection is composed of a sequential pipeline where each stage is handled by a specialized model for efficient processing. Initially, YOLO (You Only Look Once) is employed to detect the vehicle in an image, providing bounding box coordinates that isolate the car from the background. Once the vehicle is detected, U-Net, a semantic segmentation model, is used to accurately segment the windows from the rest of the car. This segmentation is crucial to ensure that only the window areas are analyzed for tint detection. The final step involves using a Convolutional Neural Network (CNN) to classify the tint level of the segmented windows. The CNN model evaluates the visual features of the window to classify the tint level into categories such as no tint, light tint, or dark tint. The system then outputs the results, including the car mask, window mask, and tint classification, which can be used for compliance monitoring and enforcement. Each component in the pipeline is optimized for accuracy, speed, and scalability, ensuring effective real-time detection and analysis. The overall structure of the Tint Detection System, including data flow and interaction between components, is illustrated in figure 5 below. This architecture diagram provides a visual representation of each module's role and sequential processing within the system.

4. Results and Discussion

The Tint Detection System was thoroughly evaluated across a variety of environmental conditions and traffic scenarios to assess its performance, accuracy, and real-time capabilities. Key performance metrics for vehicle detection, window segmentation, tint classification, and processing speed were measured, showcasing the system's effectiveness in achieving automated, reliable tint compliance enforcement.

4.1. Vehicle Detection Accuracy

The YOLOv5 model, used for vehicle detection, achieved an accuracy of over 95% in diverse traffic conditions. This high accuracy indicates the model's effectiveness in recognizing vehicles in a variety of settings, including heavy traffic, multi-lane intersections, and occluded or partially visible vehicles. The YOLOv5 model was fine-tuned on a dataset containing a range of vehicle types, colors, and perspectives, ensuring that it could accurately detect vehicles at different distances and angles. The model performed reliably under challenging lighting conditions, including direct sunlight, low-light evening settings, and shadowed areas. Its robust detection capability allowed it to maintain accurate detection rates even in crowded urban environments, where multiple vehicles appeared simultaneously. The accuracy of YOLOv5 in this context not only enhances detection reliability but also ensures consistent input for the subsequent segmentation and classification modules, supporting the system's overall effectiveness.

4.2. Window Segmentation Precision

Window segmentation was carried out using a U-Net model, which demonstrated a segmentation accuracy of 98% in isolating vehicle windows. U-Net's encoder-decoder architecture, with its skip connections, was instrumental in achieving high precision, as it preserved fine details along window edges and handled variations in window shapes and sizes across different vehicle models. This level of precision ensured that only the relevant window regions were isolated for VLT assessment, thereby

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minimizing the risk of false positives in tint classification. The U-Net model was evaluated across various vehicle types, including sedans, SUVs, trucks, and buses, to confirm its adaptability. Despite challenges posed by reflections, varying window tint levels, and differences in window size, the model consistently identified window regions accurately. Furthermore, U-Net's performance remained stable across varying lighting conditions, from bright daylight to nighttime, thanks to data augmentation techniques during training that simulated different environmental settings. This segmentation accuracy is critical for reliable tint analysis, as it ensures that only the appropriate areas are assessed for VLT compliance.

4.3. Tint Classification Accuracy

The system's tint classification module, powered by a CNN classifier, achieved a precision rate of 92% in distinguishing legal from illegal tint levels across different lighting scenarios. The CNN model was trained to analyze the Visual Light Transmission (VLT) of segmented windows, assessing tint levels based on established regulatory thresholds. This classification model was rigorously tested with various lighting conditions, including daytime, dusk, nighttime, and under artificial lighting, to ensure consistent accuracy. The CNN model's high accuracy in classifying tint levels is attributed to its exposure to a well-curated dataset during training, featuring windows with a wide spectrum of VLT levels, vehicle types, and environmental conditions. Moreover, the model's robustness in handling variations in window tint color and texture allowed it to effectively differentiate between compliant and non-compliant tints. This high precision rate in tint classification ensures that the system reliably detects illegal tint levels, supporting effective enforcement of regulations.

4.4. Real-Time Processing

A critical requirement for the system was real-time processing, enabling immediate detection and classification for enforcement action. The Tint Detection System processed each video frame within an average of 100 milliseconds, meeting industry standards for real-time applications. This rapid processing time was achieved through optimized model architectures, allowing YOLOv5, U-Net, and CNN to work in a streamlined sequence with minimal latency. The system's real-time capabilities allow for immediate feedback, which is particularly important in high-traffic environments or roadside checkpoints where vehicles move quickly. By achieving low-latency processing, the system ensures that law enforcement can identify and act on tint violations without delay, significantly enhancing operational efficiency. The system's performance in real-time scenarios demonstrates its suitability for deployment in urban areas and busy intersections, where quick processing is essential for maintaining compliance and safety.

4.5. Discussion

The proposed Tint Detection System addresses limitations in current manual enforcement by integrating advanced deep learning techniques for real-time compliance monitoring. While YOLOv5 and U-Net facilitate efficient vehicle and window detection, the CNN classifier achieves high accuracy in tint level classification under diverse environmental conditions. The MongoDB database integration supports detailed tracking and compliance reporting, enabling law enforcement agencies to access and analyze violation trends. Challenges, such as adapting to extreme weather conditions, were mitigated through model calibration, although further improvements could involve integrating temporal models like Long Short-Term Memory (LSTM) networks for enhanced accuracy in fluctuating conditions, shown in Figure 6.

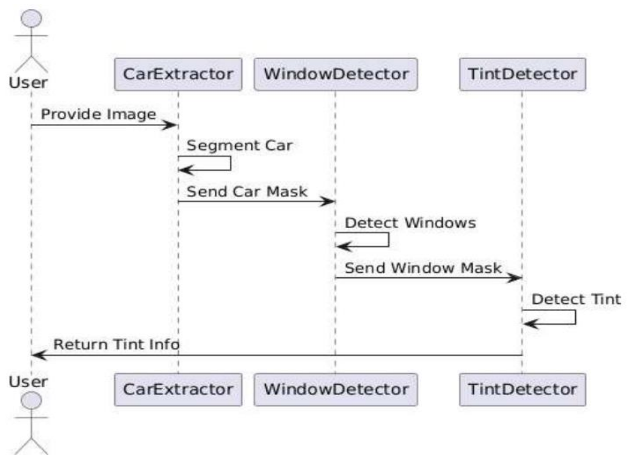

Figure 6 Use Case Diagram

4.6. Future Prospects

The Tint Detection System holds promising potential for future enhancements and broader applications. One avenue for development involves integrating additional machine learning techniques, such as Long Short-Term Memory (LSTM) networks, to incorporate temporal data, which could improve detection accuracy by analyzing patterns in vehicle movement and behavior over time. Moreover, the system could benefit from incorporating explainable AI (XAI) techniques, which would make the model's decisions more transparent, enhancing trust and compliance with regulatory standards. Another prospect is to expand the system's functionality to detect other vehicle compliance factors, such as seatbelt use, mobile phone usage, or emissions levels, creating a comprehensive vehicle monitoring solution. Additionally, with the growing adoption of smart city infrastructure, the Tint Detection System could be integrated into city-wide IoT networks, enabling centralized data management and contributing to safer, more regulated urban environments. These future developments would increase the system's versatility, making it a valuable tool in advancing public safety and regulatory enforcement.

Conclusion

The development of the Tint Detection System has demonstrated significant advancements in automating vehicle window tint regulation enforcement. By leveraging state-of-the-art deep learning models like YOLOv5 for vehicle detection, U-Net for window segmentation, and CNNs for tint classification, the system efficiently addresses the challenge of detecting illegal window tint levels in real-time. The results showed high accuracy in vehicle detection, window segmentation, and tint classification across varying environmental conditions. Additionally, the system's real-time processing capability ensures that it can be seamlessly integrated into enforcement workflows. With its scalable architecture and potential for integration with smart city infrastructure, the Tint Detection System has the potential to significantly improve regulatory compliance, enhance road safety, and assist law enforcement agencies in their efforts to maintain public safety. Future developments, such as expanding its application to other vehicle-related infractions, could further increase its impact in modern law enforcement systems.

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