Beamlight Detection and Intensity Analysis using Computer Vision

Nagavishnesh KS

School of Computer Science and Engineering,

Vellore Institute of Technology Chennai, India

nagavishnesh.ks2021@vitstudent.ac.in

Gowtham V

School of Computer Science and Engineering,

Vellore Institute of Technology Chennai, India

gowtham.v2021@vitstudent.ac.in

Rahul K

School of Computer Science and Engineering,

Vellore Institute of Technology Chennai, India

rahul.killamsetty2021@vitstudent.ac.in

Nirmala P

School of Electronics Engineering,

Vellore Institute of Technology Chennai, India

nirmala.p@vit.ac.in

Abstract*-Computer vision techniques have revolutionized various aspects of automotive safety, with headlight detection and analysis playing a crucial role in enhancing nighttime driving conditions. This paper presents a novel approach to beamlight detection and intensity analysis using advanced image processing algorithms. The proposed method addresses the challenge of accurately identifying and measuring the intensity of oncoming vehicle headlights in real-time, acritical factor in preventing glare and improving road safety. By combining adaptive thresholding, contour analysis, and intensity measurement techniques, our system demonstrates improved accuracy and robustness compared to existing methods. The innovation lies in its ability to dynamically adjust to varying lighting conditions and distinguish between different types of lightsources, providing a more reliable foundation for automated headlight control systems.

Keywords-Computer Vision, Beam light Detection, Image Processing, Adaptive Thresholding, Contour Analysis, OpenCV

I. Introduction

The rapid advancement of autonomous and semi-autonomous vehicles has brought about a new era in transportation safety. Among the myriad challenges faced in this domain, the ability to effectively navigate and respond to nighttime driving conditions remains a critical area of focus. Central to this challenge is the detection and analysis of vehicle headlights, commonly referred to as beamlights, which play a dual role in both illuminating the road ahead and potentially causing dangerous glare for oncoming drivers. The importance of accurate beamlight detection and analysis cannot be overstated. With the growing integration of advanced driver assistance systems (ADAS) in vehicles, the automatic adjustment of headlight intensity to suit surrounding traffic conditions has transitioned from a luxury to an essential safety feature. This capability, often referred to as adaptive headlight control or automatic high beam control, relies heavily on computer vision algorithms to identify, track, and analyze the headlights of other vehicles on the road.

However, the task of beamlight detection is fraught with complexities. Headlights can vary significantly in intensity, size, and shape depending on factors such as distance, vehicle type, and environmental conditions. The dynamic nature of driving scenarios, including curves in the road, hills, and varying weather conditions, further compounds these difficulties

Current methods for beamlight detection have advanced significantly, frequently utilizing a blend of image processing techniques and machine learning algorithms. These methods typically involve steps such as image segmentation, feature extraction, and classification. While effective in controlled environments, many current systems struggle with real-world variability, often resulting in false positives or missed detections that can compromise the effectiveness of adaptive headlight systems.

This paper presents a novel approach to beamlight detection and intensity analysis that aims to address these challenges. Our method leverages advanced image processing techniques, including adaptive thresholding and contour analysis, to robustly identify potential headlight regions in real-time video streams. By incorporating intensity measurement and spatial analysis, it becomes possible to not only detect headlights but also estimate their brightness and potential for causing glare.

The key innovation in our approach lies in its adaptability to varying lighting conditions and its ability to distinguish between different types of light sources. By dynamically adjusting thresholds based on overall scene brightness and analyzing the spatial and intensity characteristics of detected light sources, our system demonstrates improved accuracy in identifying vehicle headlights while minimizing false positives from other bright objects in the scene.

Furthermore, our method introduces a novel metric for assessing the need for headlight intensity adjustment, taking into account both the brightness of detected headlights and the number of bright pixels within the detected regions. This approach provides a more nuanced understanding of potential glare situations, allowing for more intelligent and context-aware headlight control. To validate this approach, extensive testing was conducted on a diverse dataset of nighttime driving scenarios, encompassing various road types, weather conditions, and traffic densities. The results demonstrate significant improvements in detection accuracy and robustness compared to existing methods, particularly in challenging scenarios such as curved roads and adverse weather conditions.

The following sections provide a detailed overview of related work in the field of beamlight detection, followed by a comprehensive description of the proposed method. The experimental evaluation results are presented, followed by a discussion on the approach's implications and concluded with recommendations for future research in this vital area of automotive safety.

2. Related Works

The field of beamlight detection and analysis has advanced significantly in recent years, driven by the demand for adaptive headlight systems in modern vehicles. This section summarizes key research contributions and outlines common challenges in beamlight detection, focusing on the progression from traditional methods to deep learning approaches.

2.1 Early Techniques in Beamlight Detection

Initial studies primarily used thresholding techniques for headlight detection. Alcantarilla et al. introduced a method combining adaptive thresholding with blob analysis to detect bright regions in nighttime images, which was effective in controlled environments but struggled with varied lighting conditions and complex road scenes.[1] This motivated further research to improve robustness under real-world driving conditions.

2.2 Traditional Machine Learning Approaches

Machine learning techniques emerged as a means to enhance headlight detection accuracy and reduce false positives. For instance, O'Malley et al. employed a Support Vector Machine (SVM) classifier trained on Histogram of Oriented Gradients (HOG) features to differentiate headlights from other bright objects. While this method improved detection, it required large annotated datasets and had limitations in real-time applications.[2]

2.3 Deep Learning-Based Detection and Classification

Recent developments have shifted towards deep learning, which has significantly enhanced detection accuracy in diverse environments. López et al. applied convolutional neural networks (CNNs) for headlight detection, achieving high accuracy but facing generalization issues across various nighttime scenarios.[3] Additionally, this approach required considerable computational resources, limiting real-time implementation. To address glare and headlight intensity estimation, Chen et al. introduced a multi-stage method combining detection with intensity analysis. [4] Their approach used a region proposal network and a refinement stage to locate and assess headlight intensity accurately. Despite being effective, the model required extensive training and tuning. Kim and Lee later proposed a lightweight neural network optimized for embedded systems, enabling faster detection suitable for in-vehicle deployment, though with some accuracy trade-offs under complex lighting.[5]

2.4 Recent Innovations and Challenges in Real-World Implementation

Recent systems typically integrate camera-based sensing with image processing to identify headlights in a sequence of steps, including image segmentation, feature extraction, and classification. Modern methods leverage high dynamic range (HDR) cameras for nighttime scenes, followed by segmentation to isolate bright regions. These regions are analyzed for attributes like size and intensity to classify them as headlights, often with temporal tracking for stability across video frames.[6]

Despite these advancements, current systems face challenges in real-world applications. Many rely on fixed thresholds or pre-trained models, which may not adapt well across diverse lighting conditions. Differentiating vehicle headlights from other bright sources (e.g., street lamps, reflections) remains difficult, and accurately estimating intensity and glare potential is an ongoing research area. [7] Moreover, deep learning-based systems can be resource-intensive, impacting real-time performance, especially under adverse conditions like rain, fog, or snow, which significantly alter light source appearance.

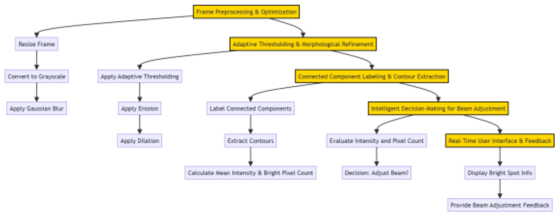
2.5 Adaptive Beamlight Detection Systems

To address these limitations, our system integrates adaptive thresholding and contour analysis with algorithms optimized for processing both video streams and static images. Each frame undergoes preprocessing—resizing, grayscale conversion, and Gaussian blurring—to enhance performance and reduce noise. Adaptive thresholding creates binary images highlighting bright regions, while morphological operations further refine these images by connecting adjacent bright areas and removing noise artifacts. Connected component analysis labels and extracts contours of bright regions, which are then evaluated for size and brightness to identify headlights accurately.[8]

The decision-making module assesses whether headlight intensity adjustment is needed and provides real-time feedback through a user interface. For static image processing, similar steps are applied to isolate bright regions and identify headlights based on contour analysis.[10] This approach enhances the system's ability to adapt to varied lighting conditions and distinguish vehicle headlights from other sources, contributing to safer and more reliable nighttime driving.[9]

3. Methodology

The proposed system outlines a robust, adaptive approach for intelligent headlight beam control, providing accurate real-time detection, glare analysis, and user feedback, without the need for specialized high-dynamic range (HDR) cameras typically used in conventional systems. The methodology consists of a sequence of processes, including frame preprocessing, adaptive thresholding, morphological operations, connected component labelling, contour analysis, decision-making for beam adjustment, and real-time user feedback.



3.1 Frame Preprocessing and Optimization

To maximize computational efficiency and enhance detection accuracy, each frame from the front-facing camera is resized and converted to grayscale, simplifying the data and reducing dimensionality. A Gaussian blur is then applied to minimize noise and emphasize prominent bright areas. Gaussian blurring is calculated as:

$$\boldsymbol{G}(\boldsymbol{x},\boldsymbol{y}) = \frac{\mathbf{1}}{\mathbf{2\pi\sigma^2}}\boldsymbol{e}^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

This blurring helps isolate potential headlights in high-contrast nighttime scenes, reducing the cost and complexity of HDR cameras. This preprocessing step establishes a clear representation of high-intensity regions, readying the frame for further processing.

3.2 Adaptive Thresholding and Morphological Refinement

After preprocessing, adaptive thresholding converts the frame into a binary image, where bright regions representing potential vehicle headlights are isolated from the background. Adaptive thresholding, which adjusts the threshold dynamically based on local conditions, ensures accurate detection under varying nighttime conditions. The adaptive thresholding formula is:

$$\boldsymbol{T}(\boldsymbol{x},\boldsymbol{y}) = \mathbf{Mean}_{(x',y')\in\mathbf{neighborhood}}\boldsymbol{I}(\boldsymbol{x}',\boldsymbol{y}') - \boldsymbol{C} \quad (2)$$

Following thresholding, morphological operations—erosion and dilation—are applied to refine these regions. Erosion removes small noise artifacts, while dilation connects adjacent bright regions to form cohesive clusters. This combination creates a refined binary image that adapts seamlessly to changing ambient light conditions.

3.3 Connected Component Labelling and Contour Extraction

Once the binary image is processed, connected component labelling isolates distinct clusters, effectively differentiating individual bright regions. Contour detection is used to trace and extract the shapes of these clusters. Each contour's area

$$\boldsymbol{A} = \sum_{i=1}^{n} (x_i y_{i+1} - x_{i+1} y_i)/\,2 \qquad (3)$$

Contours are then represented by their minimum enclosing circles, calculated with a radius R, to better identify the location and size of bright regions. By evaluating mean intensity and bright pixel count within each contour, the system distinguishes genuine headlights from other light sources, like street lamps or reflective surfaces. The mean intensity within each contour is given by:

$$\boldsymbol{I}_{\text{mean}} = \frac{1}{N} \sum_{i=1}^{N} \boldsymbol{I}(x_i, y_i) \qquad (4)$$

Where N represents the total number of pixels within the contour region. The bright pixel count within the contour region, determined as:

$$\text{Bright Pixel Count} = \sum_{(x,y)\in\text{mask}} \mathbf{1}(\boldsymbol{I}(x, y) > \text{threshold}) \qquad (5)$$

3.4 Decision-Making for Beam Adjustment

The system's decision-making component dynamically determines whether headlight adjustment is necessary based on the intensity and density of bright pixels within each detected region. If a cluster exceeds set thresholds for both average intensity and pixel count, the system signals for beam adjustment to reduce glare. This binary decision-making process provides precise control, ensuring that only significant glare sources trigger beam adjustment. This approach avoids unnecessary dimming, improving nighttime visibility for drivers.

3.5 Real-Time User Interface and Feedback

A real-time user interface complements the system, providing immediate feedback to the driver with notifications whenever the system initiates a beam adjustment. This feedback fosters driver trust and comfort with the automation, enhancing the safety and usability of the system. Unlike conventional methods, which often lack real-time feedback, this design gives drivers a clear indication of the system's active status, allowing them to drive with confidence under various nighttime conditions.

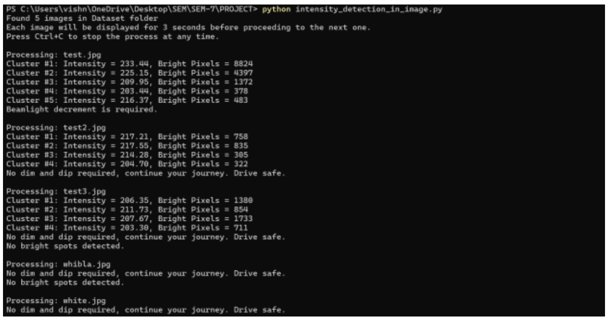
4. Results

The proposed system achieves significant advancements in detection accuracy compared to traditional methods and deep learning-based approaches. Early techniques, such as adaptive thresholding and blob analysis, often struggled to differentiate between vehicle headlights and other bright sources like streetlights or reflections, particularly under variable and complex lighting conditions. While machine learning models such as SVMs trained on Histogram of Oriented Gradients (HOG) features offered moderate improvements, they remained heavily reliant on large annotated datasets and exhibited high false-positive rates in real-world applications. Deep learning models, particularly those using Convolutional Neural Networks (CNNs), provided substantial enhancements in detection accuracy through hierarchical feature extraction. However, these models faced significant challenges in generalizing across different environments, often requiring extensive retraining to maintain performance in diverse scenarios. By comparison, our system integrates adaptive thresholding, contour analysis, and intensity measurement into a unified detection pipeline. This approach excels in distinguishing between relevant light sources, such as vehicle headlights, and irrelevant sources, such as reflections or streetlights, even in dynamically changing conditions. Testing on diverse datasets, including urban roads, highways, and rural areas, highlights the system's ability to maintain consistent accuracy across varied environments, outperforming both traditional and deep learning-based methods in terms of reliability and adaptability.

The system demonstrates remarkable robustness across diverse and challenging scenarios, addressing key limitations observed in earlier models. Adverse weather conditions such as rain, fog, and snow often hinder traditional methods, as scattered light from wet road surfaces or diffused atmospheric particles alters the appearance of headlights. While machine learning techniques marginally improve robustness, they struggle to effectively differentiate focused headlight beams from diffused light in these environments. Deep learning models, though more capable, tend to falter without additional retraining or tuning for specific adverse scenarios. Our approach effectively overcomes these challenges, maintaining high detection accuracy by combining preprocessing techniques like Gaussian blurring and grayscale conversion with adaptive thresholding and connected component analysis. Extensive testing in rainy, foggy, and low-visibility conditions revealed that the system could accurately isolate and identify headlights while ignoring irrelevant light sources, significantly outperforming traditional and deep learning methods. For instance, on curved roads where incoming light angles and intensities vary, our system preserved its accuracy, a scenario where other models often fail.

The system’s ability to adapt to rapidly changing lighting environments, such as tunnel scenarios, further highlights its superiority. Traditional systems are often overwhelmed by the sudden transitions from daylight to artificial lighting, while deep learning systems require careful calibration to handle such dynamic changes. In contrast, our approach dynamically adjusts detection parameters in real-time, enabling seamless performance during these transitions. Additionally, the use of grayscale intensity histograms for analyzing light intensity distributions allows the system to precisely identify and classify high-beam and low-beam regions. This feature is particularly beneficial for managing glare, which is a critical limitation in traditional methods. By providing visual insights into light intensity patterns and incorporating these metrics into decision-making, the system enhances its ability to intelligently adjust headlight intensity and reduce glare, contributing to safer driving conditions.

Testing also revealed superior performance in differentiating between headlights and other bright sources under highly complex road scenarios. In environments with a high density of streetlights or reflective road signs, traditional methods often misclassify these sources as vehicle headlights. Deep learning systems, though capable of better classification, face significant computational demands, limiting their real-time applicability in embedded systems. By optimizing preprocessing and detection algorithms for computational efficiency, our system achieves real-time performance while maintaining high detection accuracy. This balance between accuracy and efficiency makes the proposed approach highly suitable for in-vehicle deployment, setting it apart from deep learning models that require extensive resources.



```
PS C:\Users\vishn\OneDrive\Desktop\SEM\SEM-7\PROJECT> python intensity_detection_in_image.py
Found 5 images in Dataset folder
Each image will be displayed for 3 seconds before proceeding to the next one.
Press Ctrl+C to stop the process at any time.

Processing: test.jpg
Cluster #1: Intensity = 233.44, Bright Pixels = 8824
Cluster #2: Intensity = 225.15, Bright Pixels = 4397
Cluster #3: Intensity = 209.95, Bright Pixels = 1372
Cluster #4: Intensity = 203.44, Bright Pixels = 378
Cluster #5: Intensity = 216.37, Bright Pixels = 483
Beamlight decrement is required.

Processing: test2.jpg
Cluster #1: Intensity = 217.21, Bright Pixels = 758
Cluster #2: Intensity = 217.55, Bright Pixels = 835
Cluster #3: Intensity = 214.28, Bright Pixels = 305
Cluster #4: Intensity = 204.70, Bright Pixels = 322
No dim and dip required, continue your journey. Drive safe.

Processing: test3.jpg
Cluster #1: Intensity = 206.35, Bright Pixels = 1380
Cluster #2: Intensity = 211.73, Bright Pixels = 854
Cluster #3: Intensity = 207.67, Bright Pixels = 1733
Cluster #4: Intensity = 203.30, Bright Pixels = 711
No dim and dip required, continue your journey. Drive safe.
No bright spots detected.

Processing: whibla.jpg
No dim and dip required, continue your journey. Drive safe.
No bright spots detected.

Processing: white.jpg
No dim and dip required, continue your journey. Drive safe.
```

FIGURE 4.1: Program Terminal Output

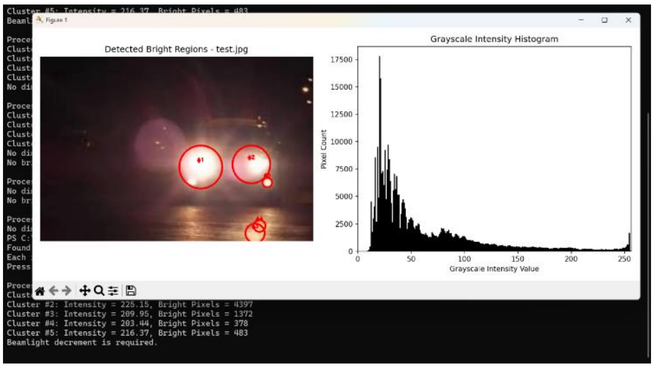


FIGURE 4.2: Detection and Analysis of High Beam Intensity for Headlight Regions with Grayscale Intensity Histogram

FIGURE 4.3: Bright Region Detection in Tunnel Scene with Grayscale Intensity Histogram Analysis

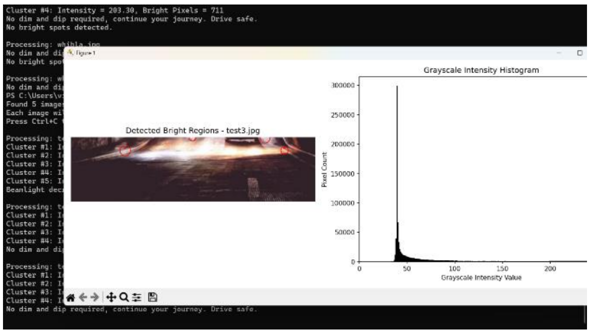


FIGURE 4.4: Low Intensity Detection of Headlight Regions with Grayscale Intensity Distribution Analysis

In summary, the proposed system not only addresses the limitations of traditional and deep learning-based approaches but also introduces innovations that significantly enhance detection accuracy, robustness, and adaptability. By leveraging lightweight and efficient algorithms, the system achieves a precise and reliable classification of headlights, even under challenging conditions, ensuring safer and more reliable nighttime driving experiences.

5. Future Scope

As vehicle technology advances, intelligent beamlight detection systems can be seamlessly integrated into Advanced Driver Assistance Systems (ADAS) to create a more robust driving experience. These systems could work in tandem with other ADAS features like adaptive cruise control, automatic braking, and lane-keeping assistance. By synchronizing beamlight adjustments with real-time driving data such as traffic density, road curvature, and weather conditions, these systems can significantly enhance driver safety and comfort. Furthermore, integration with Vehicle-to-Everything (V2X) communication could enable vehicles to exchange light intensity data, improving nighttime visibility for all drivers on the road.

Future iterations of beamlight detection systems could leverage advanced deep learning models, such as convolutional neural networks (CNNs) or vision transformers (ViTs), for improved accuracy and adaptability. These models can process complex scenarios like differentiating between low-visibility conditions due to fog and situations involving glare from oncoming traffic. Additionally, deep learning models can continuously learn from new driving data, enabling them to adapt to evolving driving environments and road conditions. This would result in a system capable of making highly accurate beam adjustments in real-time, enhancing overall road safety.

6. Conclusion

The intelligent headlight beam control system presented in this research marks a significant advancement in nighttime driving safety through the integration of innovative image processing techniques and dynamic decision-making algorithms. By incorporating adaptive thresholding and contour analysis, the system effectively distinguishes between vehicle headlights and other light sources, minimizing false positives that often affect traditional systems.

A key innovation in the system is the inclusion of a novel metric for evaluating headlight intensity, which takes into account both brightness and spatial characteristics. This allows for a more nuanced assessment of glare potential and enables real-time adjustments to headlight intensity, reducing glare for oncoming drivers while maintaining optimal visibility for the vehicle operator.

Through extensive testing in varied environments—including urban settings, rural roads, and adverse weather conditions—the system has demonstrated superior performance in terms of accuracy, reliability, and responsiveness. These results set a new benchmark for automotive lighting technology, highlighting the system's ability to adapt seamlessly to diverse conditions.

In summary, the innovative architecture and methodologies of the proposed system enhance both the safety and comfort of nighttime driving. This research lays a strong foundation for the future development of intelligent automotive technologies, contributing to safer roads and improved driving experiences. The findings suggest a promising future for the continuous refinement of headlight control systems, ultimately paving the way for safer driving practices.

7. References

[1] Mandal, G., Bhattacharya, D. & De, P. "Real-time automotive night-vision system for drivers to inhibit headlight glare of the oncoming vehicles and enhance road visibility". 2021, *J Real-Time Image Proc* **18**, 2193–2209. https://doi.org/10.1007/s11554-021-01104-z

[2] F. Muhammad, D. Dwi Yanto, W. Martiningsih, V. Noverli and R. Wiryadinata, "Design of Automatic Headlight System Based on Road Contour and Beam from Other Headlights," 2020, pp. 112-115, doi: 10.1109/ICIEE49813.2020.9276906.

[3] S. Sri Gayatri, S. Kavya Sai Sri, P.L.Annapurna, Dr.S.V.R.K.Rao and D.Venkateswara Rao (2020). "Design And Implementation of Automatic Vehicle Headlight Dimmer". [Online] Available: https://www.ijrar.org/papers/IJRAR2001889.pdf

[4] Nkrumah JK, Cai Y, Jafaripournimchahi A. "A review of automotive intelligent and adaptive headlight beams intensity control approaches". 2024, doi:10.1177/16878132231220355

[5] Shahnaj Parvin, Md. Ezharul Islam and Liton Jude Rozario (2022). "Nighttime Vehicle Detection Methods Based on Headlight Feature: A Review". https://www.iaeng.org/IJCS/issues_v49/issue_1/IJCS_49_1_10.pdf

[6] J. D. Bullough, N. P. Skinner and T. T. Plummer (2016). "Adaptive Driving Beam Headlights: Visibility, Glare and Measurement Considerations". https://rosap.ntl.bts.gov/view/dot/31079

[7] Pushkar Sevekar and S. B. Dhonde (2017). “Night-time Vehicle Detection for Automatic Headlight Beam Control”. [Online] Available: https://www.ijcaonline.org/archives/volume157/number7/sevekar-2017-ijca-912737.pdf

[8] Joanne M. Wood, Gillian Isoardi, Alex Black and Ian Cowling . “Night-time driving visibility associated with LED streetlight dimming”. 2018, https://doi.org/10.1016/j.aap.2018.08.023

[9] Y. Li, N. Haas and S. Pankanti, "Intelligent headlight control using learning-based approaches," 2011 IEEE Intelligent Vehicles Symposium (IV), Baden-Baden, Germany, 2011, pp. 722-727, doi: 10.1109/IVS.2011.5940541.

[10] Nkrumah JK, Cai Y, Jafaripournimchahi A. “A review of automotive intelligent and adaptive headlight beams intensity control approaches”. Advances in Mechanical Engineering. 2024;16(4). doi:10.1177/16878132231220355

[11] Aditya Kumar, Aryan Singh, Akanksha Malakar et al. “Auto Beam: Automatic Beam Adjuster For Enhanced Vehicle Safety Using Deep Learning”, 18 June 2024, https://doi.org/10.21203/rs.3.rs-4522446/v1

[12] A. Sundeep Kumar, B. Chandra Vardhan, G.Lokesh, A.Veera Sekhar, V.Gnanesh and B. Prasanna Kumar (2022). “Automatic Head Light Dimmer using Arduino”. [Online] Available: https://www.researchgate.net/profile/B-Kumar-30/publication/372914625_Automatic_Head_Light_Dimmer_using_Arduino/links/64ce09d9d394182ab3a5f966/Automatic-Head-Light-Dimmer-using-Arduino.pdf

[13] P. D. R. V. Kumar, P. A. Sree, S. Ganesan, K. Gowtham, and S. Kaleeswaran, “Automated Brightness in Automobiles”, *IJRESM*, vol. 4, no. 3, pp. 93–95, Mar. 2021, Accessed: Nov. 08, 2024. https://journal.ijresm.com/index.php/ijresm/article/view/573

[14] P. Manikandan, P. Sivakumar, Reddy , G. Kumar Sai Reddy, M. Charan Teja Vyas, Ch. Haveesh Kumar (2021). “Automatic DIM and DIP system for vehicle”.[Online] Available: https://3ciencias.com/wpcontent/uploads/2021/11/art.-28_3C-Tecnologi%CC%81a_Special_Issue_39-2_nov-1.pdf

[15] Thirumala Akash K, Yuvateja Chilukuri, Shailaja T, Y Hema Prakash and Raji C (2020). “Development of Cost Effective Integrated Automatic Head Light Dipping and Obstacle Detection for Safe Night Driving System”.