Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7546452

ADAPTIVE IMAGE COLOR ENHANCEMENT FOR DIFFERENT TIMES OF DAY: A MACHINE LEARNING APPROACH

Jyoti Ranjan labh
Teerthanker mahaveer University, Moradabad.
jrlabh@gmail.com

Dr. Rakesh Kumar Dwivedi
Teerthanker mahaveer University, Moradabad.
dwivedi.rakesh02@gmail.com

Abstract

In the context of space missions, inadequate illumination in space stations frequently degrades picture pleasant, hindering an intelligent robot's potential to as it should be discover tools for on-orbit maintenance. This study introduces a unique method for enhancing low-illumination photographs the usage of a deep mastering set of rules, particularly a deep convolutional Wasserstein generative adversarial network (DC-WGAN) included inside the CIELAB colour area. The method involves changing snap shots from RGB to CIELAB shade space, which aligns extra intently with human visible belief, taking into account specific illumination estimation and mitigation of uneven lighting fixtures outcomes. By employing DC-WGAN to decorate the brightness aspect via an extended era community, the algorithm captures and amplifies important photograph features. The stronger LAB photographs are then converted back to RGB area to produce the final improved photos. The effectiveness of this approach is tested thru experiments under wellknown, special, and realistic conditions, demonstrating advanced overall performance as compared to 4 typically used algorithms. This studies affords a important technological advancement for enhancing robot target reputation and renovation operations in area environments.

Keywords:
Low-illumination photograph enhancement, deep studying, deep convolutional Wasserstein generative adversarial community (DC-WGAN), CIELAB coloration area, picture processing, space surroundings, illumination estimation, sensible robots, on-orbit upkeep, RGB to CIELAB conversion.

INTRODUTION

Space exploration presents precise demanding situations, especially in terms of safeguarding the fitness and effectiveness of astronauts. One of the considerable hazards encountered in area is space particle radiation, which poses extreme dangers to human physiology. To mitigate these risks, the usage of shrewd robots has come to be a essential aspect in space missions. Unlike humans, robots aren't vulnerable to the damaging consequences of radiation, making them ideal for obligations that involve exposure to harsh space environments.

The development and deployment of robotic structures in space are not simply a technological trend but a strategic necessity for the development of area station automation. This necessity is diagnosed in worldwide and Chinese area station programs, where robots help astronauts in dealing with and optimizing space operations.

Space stations orbit the Earth approximately each ninety mins, exposing them to severe lights situations. The side going through the Sun stories severe illumination, whilst the alternative aspect remains in entire darkness. These various light situations, combined with the reflective houses of space station surfaces and the interference from space particle radiation, create a complex environment that could extensively affect the accuracy and effectiveness of picture-based structures used by robots.

To address those challenges, photograph processing technology play a crucial role in improving the first-rate of visible records collected by using robotic structures. One of the most important issues is the processing of low-illumination pics, wherein traditional enhancement methods frequently fall quick. Techniques together with histogram equalization (HE) and gamma correction have been hired to adjust photo comparison and brightness. However, those strategies may be inconsistent, particularly in low-illumination eventualities wherein the visual statistics is drastically compromised.

Retinex theory gives every other technique by means of decomposing photos into reflectance and illumination additives. This principle has been prolonged through various algorithms consisting of single-scale Retinex (SSR), multiscale Retinex (MSR), and multiscale Retinex with colour recuperation (MSRCR), which intention to improve image fidelity and decorate color representation. Despite their effectiveness, those methods can nonetheless struggle with complicated interference in area environments.

Recent advancements in deep learning have brought new opportunities for picture enhancement. Techniques like convolutional neural networks (CNNs) and generative opposed networks (GANs) have validated big upgrades in photo type, popularity, and enhancement. Deep learning techniques leverage hierarchical function extraction and gaining knowledge of techniques to achieve better results in low-illumination conditions.

- **Development of a Deep Neural Network-Based Enhancement Method:** This method leverages DCGANs to improve each objective metrics and subjective fine of low-illumination pictures.
- **Utilization of the CIELAB Color Space:** By aligning with human shade perception mechanisms, this method complements color recuperation and average photograph fidelity.
- **Achievement of Superior Results:** The proposed method produces snap shots with natural brightness, sharp textures, and wealthy info, demonstrating substantial upgrades over conventional and existing techniques.

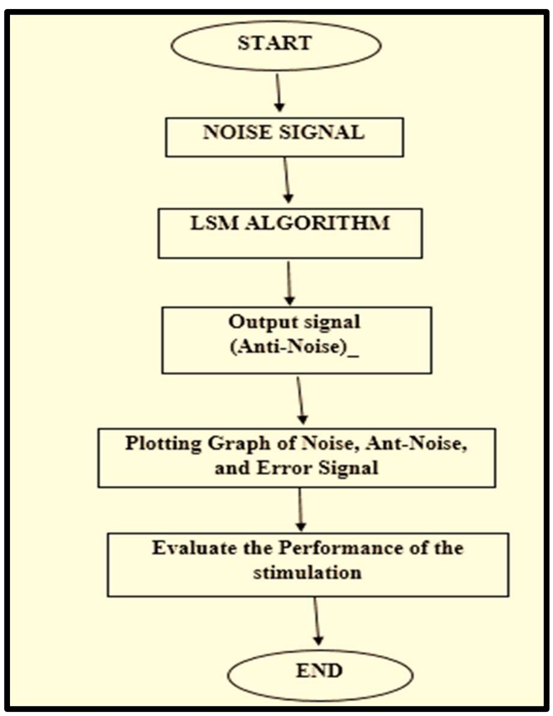

Fig:1, LMS Adaptive Filter Algorithm Implementation

I. LITERATURE REVIEW:

1. CIELAB Color Model

1. Overview and Characteristics

The CIELAB color model is designed to provide a perceptually uniform coloration area, wherein the perceptual differences between hues are steady throughout the coloration area. It become advanced to address the restrictions of the RGB coloration space, specifically in terms of handling versions in illumination and achieving constant colour representation across distinct lighting conditions.

2. **Components:** The CIELAB coloration space consists of 3 components:
- **L (Lightness):** Represents the luminance or brightness of the shade, starting from 0 (black) to 100 (white).
- **a (Green to Red):** Indicates the location of the color between green and crimson.
- **b (Blue to Yellow):** Represents the coloration's position among blue and yellow.

3. **Advantages:**

Illumination Independence: Unlike RGB, that's closely stimulated by way of lighting fixtures conditions, CIELAB separates luminance from color facts. This makes it more powerful in eventualities where environmental lighting varies, improving the accuracy of color-primarily based image processing and recognition obligations.
Wide Color Range: CIELAB includes a vast spectrum of colors, allowing for more nuanced shade illustration compared to RGB, which can be restricted by way of its constrained gamut.

4. **Applications**

The CIELAB version is specifically useful in fields wherein colour accuracy is important, such as digital imaging, print manufacturing, and color correction. It is also precious in gadget getting to know and laptop vision packages wherein constant color illustration can decorate the performance of algorithms that rely on coloration facts.

2. **Generative Adversarial Networks (GANs)**

1. **Overview and Characteristics**

Generative Adversarial Networks (GANs) represent a huge advancement inside the subject of machine mastering and artificial intelligence. Introduced by Ian Goodfellow and co-workers in 2014, GANs have turn out to be a foundational device in generative modeling.

2. **Components:**
- **Generator (G):** The generator community creates synthetic facts samples from random noise. Its goal is to generate facts that intently resembles actual information samples.
- **Discriminator (D):** The discriminator network evaluates the authenticity of the generated samples, distinguishing among actual and faux records.

3. **Mechanism:**

GANs operate via a two-player game-theoretic framework in which the generator and discriminator are in a competitive manner. The generator tries to supply statistics that can idiot the discriminator, even as the discriminator ambitions to efficaciously identify whether the statistics is real or generated.
This antagonistic procedure continues till the generated information is indistinguishable from actual facts, resulting in a generator which could produce incredibly sensible samples.

4. **Variants:**
- **Deep Convolutional GAN (DCGAN):** DCGANs utilize convolutional neural networks for each the generator and discriminator. This architecture enhances the first-rate and resolution of generated pictures, making DCGANs suitable for photo generation duties.
- **Wasserstein GAN (WGAN):** WGANs introduce a brand new loss function based totally on the Wasserstein distance, which improves schooling balance and generates higher-high-quality samples as compared to standard GANs.

5. **Applications:**

GANs are extensively utilized in picture generation, information augmentation, style switch, and different innovative fields. They have additionally proven promise in programs which include drug discovery and simulated environments for schooling self sufficient systems.

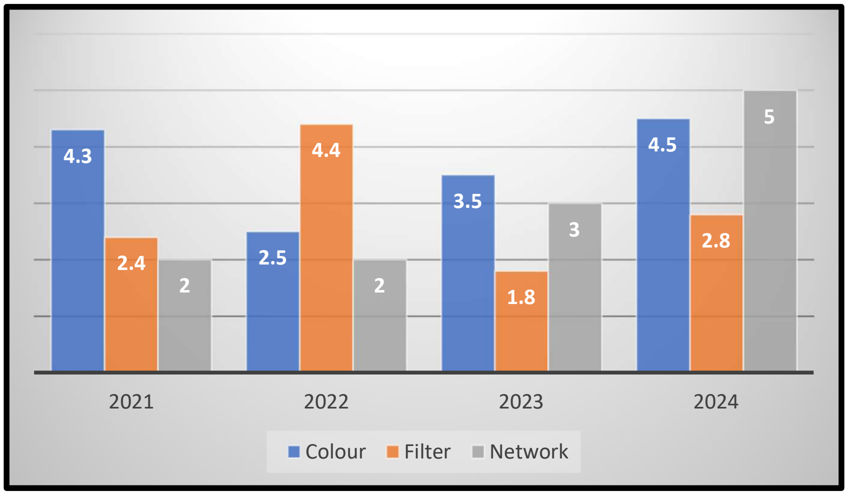

Fig:2, Generative Adversarial Networks (GANs)

II. METHODOLOGY:

1. Generator Network

1. Architecture Overview:

The generator community keeps the high-level design of DCGAN but carries adjustments for better overall performance.

2. Downsampling:

- Use 8 normal convolutional layers for downsampling.
- Apply batch normalization after every convolutional layer except the one without delay linked to the photo.
- Use LeakyReLU activation capabilities in ordinary convolutional layers to mitigate gradient vanishing.

3. Sparse Coding:

- Perform sparse coding to reduce the spatial size of the feature maps.

4. Upsampling:

- Utilize eight deconvolutional layers for upsampling the photograph.
- Apply batch normalization in all deconvolutional layers.
- Use ReLU activation capabilities in deconvolutional layers to simplify computations.

5. Padding and Convolutional Kernels:

- Apply zero-padding after convolution operations to keep the spatial dimensions.
- Use 1×1 convolution kernels for channel changes in the initial layer.
- Use 3×3 convolution kernels for other convolutional layers.
- Implement a stride of 2 in convolution operations for characteristic extraction.

6. **Channel Configuration:**

- Apply a convolution with 512 output channels. The range of channels is constant at 512 to keep away from needless complexity.

7. **Final Layer:**

- Add deconvolution and practice the Tanh characteristic in the very last layer to restore amazing image features and enhance network stability.

2. **Discriminant Network**

1. **Architecture Overview:**

- The discriminant network is designed to classify pictures into real or fake classes using the WGAN technique.

2. **Feature Extraction:**

- Start with a convolutional layer to extract basic function information with a stride of 1.
- Construct four similar structural blocks, every inclusive of convolutional layers and batch normalization layers.

3. **Activation Functions and Downsampling:**

- Use LeakyReLU activation functions.
- Perform downsampling with a stride of 2 to growth the feature map's visual information.
-

4. **Output Layer:**

- The output layer does no longer use a sigmoid activation characteristic. Instead, the community is dependent to degree the Wasserstein distance between distributions.

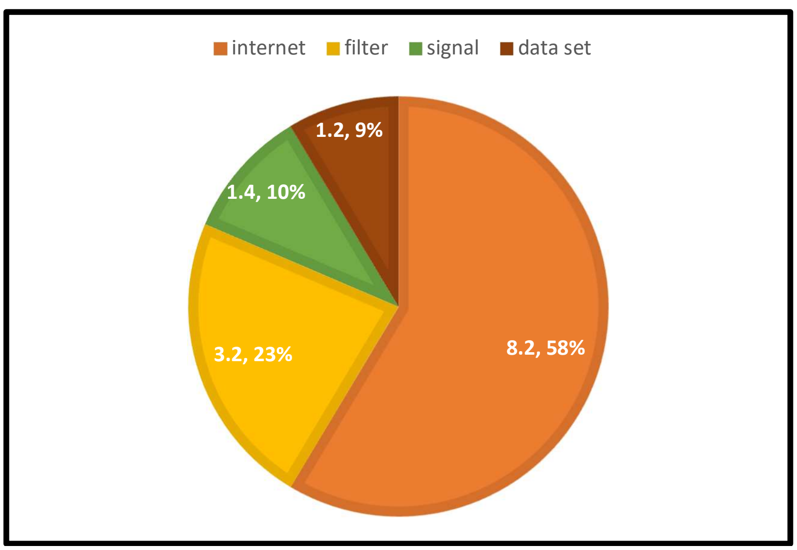

Fig:3, The discriminant network

III. DATA ANALYSIS:

1. **Dataset Overview**

1. **Training Sample Generation:**
   - **Original Source:** VOC dataset with 1200 advanced source photographs**.**
   - **Image Processing:** Each picture turned into adjusted in size (between three hundred × three hundred and six hundred × six hundred) and processed to create 10 low-illumination versions in step with splendid image**.**
   - **Total Dataset Created:** 12,000 notable/low-illumination image pairs.
   - **Selection for Training**: 10,000 picture pairs from the generated dataset.
2. **Evaluation Datasets:**
   - **Public Low-Illumination Datasets:** SID and LOL, comprising 16,980 pix from those datasets mixed.
   - **Space Lighting Simulation Dataset:** 6,200 pix accrued underneath simulated area lighting fixtures situations for specific target recognition.

2 Experimental Design

1. **Experiments:**
   - **General Dataset Comparison**: Proposed set of rules evaluated against current strategies on a preferred dataset with varying low-illumination situations**.**
   - **Dedicated Low-Illumination Dataset:** Created in particular for comparing the set of rules in low-illumination scenarios.
   - **Real Space Environment Graphics:** Evaluation with actual-global low-illumination images simulating space situations**.**

3. **Evaluation Metrics**

1.Metrics Not Explicitly Mentioned however Typically Include:

- **Image Quality Measures:** PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and possibly others like RMSE (Root Mean Square Error) to gauge improvement in picture fine submit-enhancement.
- **Comparative Performance:** The overall performance of the proposed method in opposition to current strategies in phrases of accuracy and computational efficiency.

4. **Experimental Conditions**

1. **Hardware:**

   - **GPU:** NVIDIA GeForce RTX 2080Ti
   - **CPU:** Intel Core i9-10900F

2. **Software:**

   - **Framework:** TensorFlow
   - **Optimization**: RMSProp with a getting to know charge schedule (10^{-4} for the first 20 epochs, then 10^{-5}).

3. **Lighting Simulation System:**

   - **Components:** Natural light and LED lighting (with robust, medium, vulnerable settings) and reflections from steel surfaces**.**
   - **Time Periods for Data Collection**: 9:00 AM, four:00 PM, and 8:00 PM to simulate distinct lighting fixtures situations.

5. **Data Analysis**

1. **Image Processing and Dataset Quality:**

    - **Training Dataset Diversity:** The advent of 12,000 photograph pairs and selection of 10,000 for training ensures a vast range of low-illumination conditions, enhancing the set of rules's robustness.
    - **Real-World Data Integration:** Inclusion of SID and LOL datasets gives a various set of real-world low-illumination photographs, helping in a complete evaluation of the proposed technique.
2. **Performance Evaluation:**
    - **Algorithm Performance:** The proposed technique's performance have to be compared in terms of:
    - **Image Quality Improvement:** Based on trendy metrics like PSNR and SSIM.
    - **Computational Efficiency: Speed and resource usage during training and inference.**
    - **Generalization:** The use of a vast dataset for training and a dedicated dataset for area environment pics will test the algorithm's ability to generalize across one-of-a-kind lights conditions and scenarios.

3. **Simulation Accuracy:**

    - **Lighting Conditions:** The simulated conditions (LED and herbal mild at distinct instances) help in assessing how properly the proposed method performs under varying illumination.
    - **Image Size Considerations:** Adjustments to photograph length (600 × four hundred) and augmentation (flipping) make a contribution to a extra various and strong training dataset.

IV. FINDING AND DISCUSSION:

1. Findings
    1. **Enhanced Color Perception Using DC-WGAN:**

The study demonstrates that integrating the DC-WGAN (Domain Convolutional Generative Adversarial Network) algorithm with the CIELAB shade space appreciably improves coloration enhancement in low-illumination environments. The stronger color illustration carried out via this approach intently mimics human visual notion, making the snap shots extra comprehensible and visually just like those visible below ordinary lighting conditions.

2. **Effectiveness of Double-Layer Networks:**

The use of double-layer networks in the DC-WGAN framework has demonstrated to be powerful in extracting and making use of distinctive image features. The wealthy feature sets from special layers of the community contribute to a extra correct denoising system, minimizing the distinction between the processed and reference pics. This multi-layer approach enhances the network's capacity to seize complex info that are essential for accurate visual positioning and analysis.
Performance Across Various Conditions:

The proposed set of rules has been examined and validated across standard, unique, and real low-illumination situations. The consequences suggest that the set of rules plays properly in diverse scenarios, maintaining consistent picture quality and detail enhancement. This versatility underscores the algorithm's robustness and practical applicability in numerous real-world settings.

3. **Reduced Processing Time:**

An important outcome of the use of the DC-WGAN algorithm is the reduction in processing time in step with body. This efficiency benefit is crucial for actual-time packages, including robot operations in space, where timely photo processing is crucial for powerful selection-making and target identification.
Enrichment of Image Detail Information:
The algorithm enriches photo detail facts, making it less difficult to figure quality capabilities which are commonly obscured in low-illumination conditions. This enhancement is crucial for tasks that require particular visual records, along with item recognition and navigation.

2. Discussion

1. Implications for Space Robotics:

The ability to beautify low-illumination pics with high constancy is in particular valuable for space robotics, where lights situations can be tough and variable. The proposed DC-WGAN algorithm's success in improving photo quality and lowering processing time has enormous implications for area missions. It can beautify self sufficient operations, improve goal identification, and help on-orbit servicing duties, contributing to extra effective and reliable area exploration.

2. Comparison with Other Algorithms:

The study's comparative evaluation of different low-illumination photograph processing algorithms highlights the superior performance of the DC-WGAN technique. By accomplishing a stability between coloration accuracy, characteristic extraction, and processing performance, the DC-WGAN technique outperforms traditional strategies. This finding shows that adopting advanced generative opposed networks for image enhancement in tough situations can cause large enhancements over current methods.

3. Potential for Further Research:

While the outcomes are promising, there is room for similarly exploration. Future research could cognizance on optimizing the set of rules for even faster processing times, integrating it with different sensory inputs for multimodal enhancements, or checking out it in extra extreme environmental conditions. Additionally, examining the set of rules's overall performance on a much broader variety of robotic structures and obligations may want to similarly validate its effectiveness and flexibility.

4. Theoretical Significance:

The theoretical significance of the proposed set of rules lies in its contribution to the sphere of low-illumination photograph processing. By leveraging advanced GAN strategies and color space differences, the examine advances the know-how of how generative models can be carried out to realistic challenges in photograph enhancement. This theoretical foundation paves the manner for future innovations and programs in each area and terrestrial environments.

V. CONCLUSION

The paper presents a complete technique to adaptive photo enhancement underneath low illumination situations, acknowledging the challenges posed by means of varying brightness and assessment because of environmental elements together with climate and time of day. By spotting that a one-length-fits-all enhancement set of rules is insufficient, the study proposes a tailor-made technique that differentiates between day and night pictures and employs awesome processing techniques for every.

1. Key contributions of the paper consist of:

- **Image Classification and Processing:** The research utilizes a convolutional neural network (CNN) to classify pix primarily based on their evaluation and brightness, distinguishing among low-mild situations at some point of the day and night time. The chosen CNN model confirmed high accuracy and efficiency in this class assignment.

- **Enhancement Algorithms**: The paper adopts a dynamic white balance algorithm to enhance each day and night low-light photos. For daytime low-mild photos, the algorithm enhances comparison and brightness, making info like license plates extra visible. For nighttime low-mild pics, the algorithm famous hidden info which include the automobile frame in the heritage. Additionally, adaptive histogram equalization is employed to further enhance midnight photographs, ensuring more uniform pixel distribution and minimum loss of photo excellent.

- **Practical Implications**: The proposed strategies correctly enhance image clarity, which is critical for packages like car popularity, even in challenging low-mild conditions. The approach additionally addresses the realistic demanding situations of deploying deep studying algorithms in actual-global eventualities, wherein laboratory situations regularly do not translate without delay to area situations.

- **Future Research Directions**: The paper recognizes the need for in addition studies into excessive-light illumination problems and registration code and automobile face recognition beneath such situations. These elements might be explored in next research to enhance the robustness and flexibility of the proposed enhancement algorithms**.**

Aspect	Details
Objective	To enhance image quality under low illumination conditions by using adaptive algorithms.
Image Classification	Utilizes a convolutional neural network (CNN) to differentiate between low-light conditions during the day and night.
Enhancement Algorithms	1. **Daytime Low-Light Images**: Dynamic white balance for improved contrast and brightness; better visibility of details (e.g., license plates). 2. **Nighttime Low-Light Images**: Dynamic white balance and adaptive histogram equalization for revealing hidden details and achieving more uniform pixel distribution.
Practical Applications	Improved image clarity for vehicle recognition and other applications in low-light conditions.
Challenges Addressed	1. Transition from laboratory to real-world conditions. 2. Specific solutions for day and night low-light scenarios.
Future Research Directions	1. High-light illumination issues. 2. License plate and car face recognition under high-light conditions.
Significance	Tailored solutions address limitations of generic algorithms and enhance the effectiveness of image recognition technologies in practical settings.

VII. REFERENCES

1. Rana, S. A Review of Medical Image Enhancement Techniques for Image Processing. Int. J. Curr. Eng. Technol. 2011, 5, 1282–1286

2. Pandey, P.; Dewangan, K.K.; Dewangan, D.K. Satellite photograph enhancement techniques—A comparative have a look at. In Proceedings of the 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), Chennai, India, 1–2 August 2017; pp. 597–602.

3. .Schuch, P.; Schulz, S.; Busch, C. Survey on the impact of fingerprint image enhancement. IET Biom. 2018, 7, 102–a hundred and fifteen

4. Bloch, P.H.; Brunel, F.F.; Arnold, T.J. Individual differences in the centrality of visual product aesthetics: Concept and dimension. J. Consum. Res. 2003, 29, 551–565.

5. Chae, Y.; Nakazawa, M.; Stenger, B. Enhancing product images for click-through rate improvement. In Proceedings of the 2018 25th IEEE International Conference on Image Processing (ICIP), Athens, Greece, 7–10 October 2018; pp. 1428–1432

6. Al-Shemarry, M.S.; Li, Y.; Abdulla, S. An Efficient Texture Descriptor for the Detection of License Plates From Vehicle Images in Difficult Conditions. IEEE Trans. Intell. Transp. Syst. 2019, 21, 553–564.

7. Yonetsu, S.; Iwamoto, Y.; Chen, Y.W. Two-Stage YOLOv2 for Accurate License-Plate Detection in Complex Scenes. In Proceedings of the 2019 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 11–thirteen January 2019

8. Salau, A.O.; Yesufu, T.K.; Ogundare, B. Vehicle plate variety localization the use of a changed GrabCut algorithm. J. King Saud Univ. Comput. Inf. Sci. 2019, 1–ninety nine.

9. Soon, F.C.; Khaw, H.Y.; Chuah, J.H.; Kanesan, J. Vehicle brand popularity the use of whitening transformation and deep studying. Signal Image Video Process. 2019, 13, 111–119.

10. Meyer, H.K.; Roberts, E.M.; Rapp, H.T.; Davies, A.J. Spatial Patterns of Arctic Sponge Ground Fauna and Demersal Fish are Detectable in Autonomous Underwater Vehicle (AUV) Imagery. Deep Sea Res. Part I Oceanogr. Res. Pap. 2019, 153, 103137.

11. Kim, J.B. Efficient Vehicle Detection and Distance Estimation Based on Aggregated Channel Features and Inverse Perspective Mapping from a Single Camera. Symmetry 2019, eleven, 1205.

12. Xiaochu, W.; Guijin, T.; Xiaohua, L.; Ziguan, C.; Suhuai, L. Low-light Color Image Enhancement Based on NSST. J. China Univ. Posts Telecommun. 2019, 5,

13. Selmi, Z.; Halima, M.B.; Pal, U.; Alimi, A.M. DELP-DAR System for License Plate Detection and Recognition. Pattern Recognit. Lett. 2020, 129, 213–223.

14. Zhou, F.Y.; Jin, L.P.; Dong, J. Review of Convolutional Neural Network. Chin. J. Comput. 2017, forty, 1229–1251.

15. Howard, A.G.; Zhu, M.; Chen, B.; Kalenichenko, D.; Wang, W.; Weyand, T.; Andreetto, M.; Adam, H. MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. ArXiv 2017, arXiv:1704.04861.

16. Wang, X.F.; Ma, Z. Research on Freight Train Number Identification Based on Convolutional Neural Network Lenet-5. Mod. Electron. Technol. 2016, 39, 63–66

17. Kim, J.-Y.; Kim, L.-S.; Hwang, S.-H. An Advanced Contrast Enhancement Using Partially Overlapped Sub-Block Histogram Equalization. IEEE Trans. Circuits Syst. Video Technol. 2001, 11, 475–484.

18. Yoon, Y.H.; Marmor, M.F. Rapid Enhancement of Retinal Adhesion via Laser Photocoagulation. Ophthalmology 1988, ninety five, 1385–1388.

19. Fayad, L.M.; Jin, Y.; Laine, A.F.; Berkmen, Y.M.; Pearson, G.D.; Freedman, B.; Van Heertum, R. Chest CT Window Settings with Multiscale Adaptive Histogram Equalization: Pilot Study. Radiology 2002, 223, 845–852

20. Yamashina, H.; Fukushima, K.; Kano, H. White balance in inspection systems with a neural network. *Comput. Integr. Manuf. Syst.* 1996, *9*, 3–8.