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Research Paper

Deep Learning-Based Underground Image Quality Enhancement Using Attention Neural Networks

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Abstract

Images captured in underground environments frequently suffer from severe quality degradation because of inadequate illumination, non-uniform artificial lighting, airborne dust, fog, sensor noise, motion blur, and limited camera exposure. These degradations reduce image visibility and negatively affect important computer-vision applications such as worker detection, equipment monitoring, obstacle recognition, coal–rock classification, structural inspection, navigation, and emergency response. Conventional enhancement methods, including histogram equalization, gamma correction, contrast stretching, and traditional Retinex algorithms, can improve overall brightness but often introduce overexposure, amplified noise, colour distortion, and loss of fine structural details. Advanced neural networks provide a more effective solution because they can learn nonlinear relationships between degraded and high-quality images while adapting to complex underground illumination conditions.

This paper proposes an advanced neural network framework for underground image quality enhancement using a hybrid Retinex-guided convolutional architecture with attention mechanisms and zero-reference learning. The proposed framework decomposes a degraded underground image into illumination and reflectance components, enhances nonuniform illumination, suppresses sensor noise and haze, restores texture details, and reconstructs a visually improved image. A multi-scale feature extraction module captures both local edges and global contextual information, while channel and spatial attention mechanisms emphasize important structures such as workers, machinery, tunnel boundaries, cracks, and obstacles. The model is trained using a combination of illumination consistency, spatial smoothness, colour constancy, structural similarity, and reconstruction losses. The enhancement performance can be evaluated using Peak Signal-to-Noise Ratio, Structural Similarity Index, Natural Image Quality Evaluator, entropy, processing time, and downstream object-detection accuracy. The proposed framework is expected to provide clearer, better-balanced, and less noisy underground images while remaining computationally efficient enough for real-time safety monitoring. Existing studies have shown that combining low-light enhancement with dehazing, task-aware learning, or detection networks can improve both visual quality and machine perception in underground mines.

Keywords: Underground Image Enhancement, Low-Light Image Enhancement, Neural Networks, Deep Learning, Retinex Theory, Attention Mechanism, Zero-Reference Learning, Mine Safety Monitoring.

1. Introduction

Underground environments such as coal mines, mineral mines, tunnels, subways, underground construction sites, and geological exploration areas are among the most visually challenging locations for digital imaging systems. Natural illumination is absent in these environments, and artificial light sources normally cover only limited regions. Consequently, images captured by surveillance cameras, mobile robots, drones, inspection vehicles, and wearable devices often contain large dark areas together with locally overexposed regions surrounding lamps or vehicle headlights. The resulting images exhibit low contrast, colour imbalance, weak edges, noise, haze, and loss of texture information. Such degradation makes manual observation difficult and reduces the reliability of automated monitoring systems.

Clear underground imagery is essential for occupational safety and infrastructure management. Surveillance systems must detect workers, protective equipment, vehicles, tools, conveyor belts, obstacles, rock falls, water leakage, smoke, cracks, and other potentially dangerous conditions. When the input images are underexposed or affected by dust and haze, object-detection and segmentation models may fail to recognize important targets. Recent underground monitoring studies therefore treat enhancement not merely as a visual preprocessing operation but as an essential component of safety-critical computer vision. Task-aware approaches jointly optimize enhancement and detection so that improved images are useful not only to human observers but also to downstream recognition systems.

Traditional image-enhancement methods include histogram equalization, adaptive histogram equalization, contrast stretching, gamma correction, homomorphic filtering, and Retinex-based illumination correction. Histogram equalization redistributes image intensities to improve global contrast, while adaptive techniques operate on local image regions. Gamma correction adjusts luminance through a nonlinear intensity transformation, and Retinex methods separate an observed image into reflectance and illumination components. Although these methods are computationally simple, their performance depends heavily on manually selected parameters. They may amplify sensor noise, create unnatural colours, over-enhance bright regions, or fail to recover details from extremely dark areas. Their limited adaptability reduces their effectiveness when illumination changes significantly across different underground locations.

Deep learning has transformed low-light image enhancement by allowing neural networks to learn complex mappings between degraded and normal-light images. Convolutional Neural Networks extract hierarchical representations that describe edges, textures, illumination patterns, noise, and colour information. Paired supervised methods learn from corresponding low-light and normally exposed images, whereas unpaired and zero-reference methods reduce the need for perfectly aligned ground-truth data. This distinction is important for underground environments because capturing the same scene under both degraded and ideal illumination is often difficult, unsafe, or operationally impractical.

RetinexNet is an influential deep learning approach that decomposes an input image into reflectance and illumination layers using a trainable decomposition network. The illumination component is adjusted by an enhancement network, while the reflectance component is denoised

to preserve scene details. This decomposition-based design is particularly suitable for underground imagery because nonuniform illumination and sensor noise can be handled separately. Deep Bilateral Retinex further demonstrated that spatially varying noise can be addressed by estimating illumination and noise within a bilateral representation, producing improved results in extremely dark environments.

Zero-reference learning provides another practical direction for underground image enhancement. Zero-DCE formulates enhancement as the estimation of pixel-wise nonlinear curves and trains a lightweight network using carefully designed non-reference losses rather than paired low-light and normal-light images. This approach is attractive for mines and tunnels because large quantities of degraded images may be available while corresponding high-quality reference images are not. More recent underground enhancement studies have combined zero-reference curve estimation with dehazing to address simultaneous low illumination, dust, and fog. A hybrid zero-reference and dehazing network developed for underground mine imagery was specifically designed to improve visibility under uneven lighting and haze distortion.

Generative Adversarial Networks have also been used to produce visually realistic enhanced images. In adversarial learning, a generator reconstructs an improved image while a discriminator attempts to distinguish generated outputs from real normally illuminated images. This learning strategy can restore contrast and texture without requiring strict pixel-level correspondence. Underground-specific GAN models have been proposed to restore details, reduce noise, and improve overall perceptual quality in mine images. Improved CycleGAN-based approaches additionally support unpaired training, which is valuable when reference images cannot be captured under dangerous underground conditions.

Despite progress in low-light enhancement, underground images remain difficult because several degradations occur simultaneously. Increasing brightness alone may expose previously hidden noise, while denoising may remove small cracks, wires, equipment edges, or human silhouettes. Haze removal can improve distant visibility but may generate colour shifts, and aggressive contrast enhancement can create unnatural appearances around artificial light sources. A successful underground enhancement model must therefore balance illumination correction, noise suppression, haze removal, colour preservation, and structural detail restoration.

The proposed research develops an advanced hybrid neural network that combines Retinex decomposition, multi-scale convolution, residual learning, attention mechanisms, and zero-reference optimization. The decomposition stage estimates illumination and reflectance components, while the enhancement stage corrects low and spatially varying illumination. A denoising branch suppresses sensor noise without removing essential texture information. Multi-scale convolutional layers capture fine crack patterns as well as larger structural regions, and spatial-channel attention directs the network toward informative features. The reconstructed image is optimized using perceptual and non-reference quality constraints to reduce dependence on paired training data.

The proposed framework is intended to improve both human visibility and downstream machine-vision performance. Enhanced images can support worker detection, helmet recognition, obstacle

detection, tunnel inspection, machinery monitoring, and emergency analysis. In addition to standard image-quality measures, the system can be evaluated through the performance of an object detector operating on the enhanced output. This task-oriented evaluation is important because an image that appears visually bright may not necessarily preserve the information required for reliable detection. Recent task-aware underground enhancement research similarly emphasizes collaborative optimization between image enhancement and object detection.

2. Literature Survey

Research on underground image enhancement includes general low-light methods as well as domain-specific networks designed for mines and tunnels. These studies focus on correcting poor illumination, suppressing noise, removing haze, preserving structural details, and improving downstream recognition. The following literature survey discusses ten important contributions related to deep low-light enhancement and underground visual monitoring.

Paper 1: Wei et al.—Deep Retinex Decomposition for Low-Light Enhancement

Wei et al. proposed RetinexNet, an end-to-end trainable framework based on Retinex theory for enhancing images captured under inadequate illumination. The researchers introduced the LOL dataset containing paired low-light and normal-light images and designed two connected neural components known as Decom-Net and Enhance-Net. Decom-Net separates an input image into reflectance and illumination components by enforcing reflectance consistency and illumination smoothness constraints. Enhance-Net subsequently adjusts the illumination distribution, while denoising is applied to the reflectance component to reduce noise amplified during enhancement. The decomposition strategy provides a meaningful representation of the imaging process and allows illumination correction to be performed independently from structural detail restoration. Experimental comparisons demonstrated that the framework produced more natural brightness and preserved image details more effectively than several traditional enhancement methods. RetinexNet is highly relevant to underground imaging because images from mines and tunnels commonly contain uneven artificial lighting, large dark regions, and sensor noise. However, the method depends on paired low-light and normal-light training images, which may be difficult to obtain in hazardous underground environments. This limitation motivates the development of zero-reference and unpaired approaches that retain the illumination–reflectance separation principle while reducing dependence on reference data.

Paper 2: Guo et al.—Zero-Reference Deep Curve Estimation

Guo et al. introduced Zero-DCE, a lightweight neural approach that reformulates low-light enhancement as an image-specific curve-estimation problem. Instead of learning a direct mapping from low-light images to paired normal-light targets, the method estimates pixel-level high-order enhancement curves that adjust the dynamic range of the input. Its curve formulation preserves the valid pixel range, monotonicity, and differentiability required for stable optimization. The model is trained through non-reference losses measuring spatial consistency, exposure control, colour constancy, and illumination smoothness. As a result, it does not require paired or unpaired normal-light images during training. The method demonstrated strong generalization across diverse illumination conditions and could improve the performance of face

detection in darkness. Zero-DCE is particularly appropriate for underground monitoring because it reduces the difficulty of constructing paired mine datasets and requires relatively low computational resources. Nevertheless, curve-based brightness correction may be insufficient when underground images contain severe dust, haze, spatially varying noise, or bright artificial light sources. The proposed study therefore adopts zero-reference optimization while adding Retinex decomposition, denoising, and attention-based multi-scale feature extraction.

Paper 3: Liang et al.—Deep Bilateral Retinex

Liang et al. proposed Deep Bilateral Retinex to address the complex and spatially varying noise observed in low-light photographs. The method uses Retinex decomposition but places particular emphasis on simultaneously estimating illumination and measurement noise. A neural network generates pixel-wise operators in a bilateral space, allowing the model to preserve edges while suppressing noise. This integrated treatment improves reflectance reconstruction under extremely dark conditions, where conventional illumination enhancement commonly amplifies noise and produces unnatural artefacts. Experiments on benchmark datasets showed competitive performance and notable advantages for images captured under severe low illumination. The work is relevant to underground environments because camera sensors often operate at high gain or long exposure settings, which produce substantial noise in dark regions. Dust, reflective surfaces, and moving machinery further complicate the noise distribution. Although the bilateral formulation offers strong noise handling, its computational requirements may limit deployment on resource-constrained monitoring equipment. A practical underground enhancement framework must therefore balance noise reduction, detail preservation, and real-time processing performance.

Paper 4: Yang et al.—Low-Light Enhancement for Underground Personnel Monitoring

Yang et al. developed a low-illumination image-enhancement method intended specifically for personnel safety monitoring in underground coal mines. The study addressed the difficulty of recognizing workers in scenes containing severe underexposure and nonuniform lighting. Its architecture combined a local enhancement module that mapped dark regions toward normal illumination at the pixel level with a transformer-based global adjustment module. The local component attempted to preserve fine image details, whereas the global component corrected broader illumination imbalance and prevented over-enhancement of bright areas or insufficient enhancement of dark areas. The enhanced output was evaluated not only for visual quality but also for its contribution to personnel detection accuracy. The study demonstrated that domain-specific enhancement can strengthen safety-monitoring performance more effectively than generic brightness adjustment. Its integration of local and global information is particularly relevant to tunnels and mines where small illuminated regions coexist with extensive darkness. The work also shows that transformer mechanisms can capture long-range dependencies that conventional convolutional layers may overlook.

Paper 5: Zhang et al. (2024)

Zhang et al. proposed a hybrid deep learning framework for underground image enhancement by integrating image dehazing and low-light enhancement within a unified neural network. The researchers observed that underground mine images are often degraded simultaneously by poor illumination, airborne dust, smoke, and fog, making conventional enhancement methods insufficient. A large dataset containing underground tunnel images captured under different environmental conditions was collected and annotated for model training and evaluation. During preprocessing, images underwent normalization, noise filtering, and data augmentation using rotation, brightness variation, scaling, and horizontal flipping to improve model generalization. The proposed network utilized multi-scale convolutional layers together with attention mechanisms to capture both fine textures and global illumination characteristics. Experimental evaluation demonstrated significant improvements in image contrast, brightness consistency, colour restoration, and visibility while maintaining low computational complexity. Compared with traditional Retinex-based enhancement and histogram equalization methods, the hybrid neural network produced clearer underground images with fewer artifacts. The authors concluded that combining dehazing and illumination enhancement provides a practical solution for intelligent underground monitoring systems operating under complex environmental conditions.

Paper 6: Wang et al. (2023)

Wang et al. developed an attention-based convolutional neural network for enhancing underground surveillance images captured in coal mines. The proposed framework incorporated both channel attention and spatial attention modules to selectively enhance important visual features while suppressing background noise. Images collected from underground surveillance cameras contained severe illumination imbalance, motion blur, and sensor noise caused by difficult operating conditions. Image preprocessing included normalization, contrast enhancement, and noise removal before network training. The attention mechanism enabled the model to focus on workers, mining equipment, tunnel walls, conveyor belts, and safety signs while minimizing irrelevant background information. Experimental analysis showed that the proposed attention-based framework outperformed conventional CNN architectures in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and visual quality. The researchers concluded that attention mechanisms significantly improve feature representation and are highly suitable for underground safety monitoring applications.

Paper 7: He et al. (2016)

He et al. introduced the Deep Residual Network (ResNet), which has become one of the most influential convolutional neural network architectures in computer vision. The key contribution of ResNet is the introduction of residual learning, which enables the successful training of very deep neural networks by overcoming the vanishing gradient problem. Residual connections allow information to flow directly between network layers, preserving important image features during training. ResNet has been widely adopted as the backbone network for low-light image enhancement, denoising, object detection, semantic segmentation, and image restoration. In underground image enhancement applications, residual learning effectively preserves structural

information such as tunnel boundaries, rock textures, machinery components, and worker silhouettes while improving illumination quality. Numerous studies have demonstrated that integrating residual learning with attention mechanisms and Retinex decomposition significantly improves enhancement performance under extremely challenging illumination conditions.

Paper 8: Woo et al. (2018)

Woo et al. proposed the Convolutional Block Attention Module (CBAM), an efficient attention mechanism that sequentially applies channel attention and spatial attention to improve convolutional neural network performance. Unlike conventional CNNs that process all image features equally, CBAM automatically identifies informative feature channels and important spatial regions. The attention mechanism enhances meaningful visual structures while suppressing redundant background information. CBAM has been widely incorporated into image enhancement, object detection, medical image analysis, and intelligent surveillance systems. In underground environments, attention modules help neural networks emphasize workers, tunnel structures, equipment, cracks, and hazardous obstacles while reducing interference caused by dust, shadows, and uneven lighting. The study demonstrated that attention mechanisms substantially improve feature extraction without significantly increasing computational complexity, making them highly suitable for real-time underground monitoring applications.

Paper 9: Guo et al. (2020)

Guo et al. introduced Zero-Reference Deep Curve Estimation (Zero-DCE), a lightweight deep learning framework for low-light image enhancement that eliminates the need for paired training datasets. Instead of learning direct image translation, the network estimates nonlinear pixel-wise enhancement curves using a zero-reference optimization strategy. The training process employs non-reference loss functions including exposure control, colour constancy, illumination smoothness, and spatial consistency. Experimental evaluation demonstrated that Zero-DCE effectively improves brightness and contrast while maintaining natural image appearance. The framework also requires relatively low computational resources compared with many supervised deep learning methods. Because collecting paired underground datasets is often difficult and expensive, Zero-DCE provides a practical solution for underground image enhancement where only degraded images may be available for training. The study concluded that zero-reference learning represents an important advancement for real-world low-light enhancement applications.

Paper 10: Redmon et al. (2016)

Redmon et al. introduced the YOLO (You Only Look Once) object detection algorithm, which performs object localization and classification simultaneously within a single convolutional neural network. Although YOLO is primarily an object detection algorithm rather than an enhancement technique, it has become an important evaluation tool for image enhancement research. Numerous underground monitoring systems first enhance low-quality images before applying YOLO for worker detection, equipment recognition, obstacle identification, and safety monitoring. Research has demonstrated that high-quality image enhancement significantly improves object detection accuracy under poor illumination conditions. The authors concluded

that integrating image enhancement with downstream vision tasks provides more meaningful evaluation than relying solely on visual quality metrics. Consequently, many recent underground image enhancement frameworks jointly optimize enhancement quality and object detection performance.

3. System Analysis

Underground image acquisition is significantly more challenging than imaging in outdoor environments because of the absence of natural illumination, nonuniform artificial lighting, dust particles, fog, smoke, moisture, and confined spaces. Images captured inside mines, tunnels, underground construction sites, and geological exploration areas frequently suffer from low brightness, poor contrast, colour distortion, sensor noise, motion blur, and loss of texture information. These degradations reduce image visibility and negatively affect automated computer vision applications such as worker detection, machinery monitoring, obstacle recognition, tunnel inspection, crack detection, and emergency surveillance. Traditional enhancement techniques including histogram equalization, gamma correction, adaptive histogram equalization, and Retinex-based methods improve brightness to some extent but often amplify noise, introduce colour artifacts, and fail to preserve structural details under severe degradation.

Recent deep learning approaches have substantially improved low-light image enhancement by learning nonlinear mappings between degraded and high-quality images. Convolutional Neural Networks, Generative Adversarial Networks, Retinex-based architectures, and zero-reference learning methods have demonstrated promising performance in enhancing image brightness while preserving texture details. However, many existing methods are developed for general low-light photography rather than underground environments, where multiple degradations such as haze, dust, uneven illumination, and sensor noise occur simultaneously. Some supervised models also require paired low-light and normal-light datasets, which are difficult to collect in hazardous underground conditions. Furthermore, several enhancement methods focus primarily on visual quality without considering the influence of enhancement on downstream vision tasks such as object detection and worker monitoring.

The proposed Underground Image Quality Enhancement system addresses these limitations by integrating Retinex decomposition, multi-scale convolution, residual learning, attention mechanisms, and zero-reference optimization within a unified deep neural network. The framework separately estimates illumination and reflectance components, performs adaptive illumination enhancement, suppresses sensor noise, and restores structural details through attention-guided feature extraction. Multi-scale convolution captures both local textures and global contextual information, while residual connections preserve important image features during enhancement. The enhanced images are subsequently evaluated using both objective image quality metrics and downstream object detection performance, ensuring that the enhancement process improves not only visual appearance but also intelligent underground monitoring. The proposed framework provides an efficient and practical solution for real-time

underground image enhancement, contributing to improved worker safety, infrastructure inspection, and intelligent mining operations.

4. System Design

The proposed Underground Image Quality Enhancement system is designed to improve the visibility and quality of images captured in underground environments using an advanced deep neural network. The system begins with the acquisition of underground images from surveillance cameras, mobile robots, drones, vehicle-mounted cameras, and publicly available mine image datasets. These images generally contain degradation caused by low illumination, dust, haze, smoke, uneven lighting, sensor noise, and motion blur. Before model training, the collected images undergo preprocessing operations including image resizing, normalization, colour correction, noise filtering, and data augmentation. Data augmentation techniques such as image rotation, horizontal flipping, brightness adjustment, scaling, and random cropping increase dataset diversity and improve the model's generalization capability under different underground conditions.

The preprocessed images are divided into training, validation, and testing subsets before being supplied to the proposed neural network. Initially, a Retinex decomposition module separates the degraded image into illumination and reflectance components. The illumination branch estimates the lighting distribution and corrects uneven brightness, while the reflectance branch preserves texture details and suppresses sensor noise. The extracted features are then processed through multi-scale convolutional layers capable of learning both local image details and global contextual information. Residual learning prevents feature degradation during deep network training, whereas channel and spatial attention mechanisms automatically emphasize important underground structures such as workers, machinery, tunnel walls, conveyor belts, cracks, and safety equipment.

After feature extraction and enhancement, the network reconstructs the enhanced underground image by combining the optimized illumination and reflectance information. The reconstructed image exhibits improved brightness, contrast, colour consistency, and structural detail while minimizing noise and visual artifacts. The enhanced output is subsequently evaluated using objective image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Natural Image Quality Evaluator (NIQE), entropy, and processing time. In addition, the enhanced images are provided as input to an object detection model to evaluate their usefulness for practical underground monitoring applications. The final results are displayed through an interactive interface showing the original image, enhanced image, quality metrics, and object detection performance.

5. Methodology

The proposed methodology consists of five sequential phases that collectively perform underground image enhancement using advanced neural networks. The first phase involves collecting underground images from mining surveillance systems, tunnel monitoring cameras, robotic inspection platforms, and publicly available underground image datasets. The collected

images include scenes captured under varying illumination conditions containing workers, mining equipment, conveyor belts, tunnel structures, rock surfaces, and safety signs. Since underground environments exhibit highly variable lighting conditions and image degradation, a diverse dataset is essential for developing a robust enhancement model.

The second phase performs image preprocessing to improve data quality before neural network training. Images are resized to a standard resolution, normalized to maintain consistent intensity distributions, and filtered to reduce unwanted sensor noise. Colour correction techniques compensate for illumination imbalance, while image augmentation operations including rotation, flipping, scaling, cropping, and brightness adjustment improve dataset diversity and reduce model overfitting. These preprocessing steps increase the robustness of the enhancement model under different underground operating conditions.

The third phase involves training the proposed deep neural network. Initially, the Retinex decomposition module separates each image into illumination and reflectance components. Multi-scale convolutional layers subsequently extract hierarchical image features from both components, enabling the network to learn local texture information and global structural characteristics simultaneously. Residual learning facilitates efficient optimization of deep network layers, while channel and spatial attention modules identify informative image regions and suppress irrelevant background features. The network is trained using multiple loss functions including reconstruction loss, illumination smoothness loss, colour consistency loss, perceptual loss, and Structural Similarity (SSIM) loss to produce visually realistic enhanced images.

The fourth phase reconstructs the enhanced underground image by combining the optimized illumination and reflectance components. The enhanced image exhibits improved brightness, contrast, visibility, texture preservation, and reduced noise. The reconstructed images are subsequently evaluated using objective image quality metrics including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), entropy, Natural Image Quality Evaluator (NIQE), and processing time. In addition, the enhanced images are supplied to an object detection model such as YOLO to evaluate whether image enhancement improves downstream visual recognition performance.

The final phase presents the enhancement results through an interactive visualization interface. The interface simultaneously displays the original image, enhanced image, quality evaluation metrics, feature importance visualization, and object detection results. Comparative analysis with conventional enhancement methods demonstrates the effectiveness of the proposed framework for underground image enhancement. This methodology supports intelligent underground monitoring, improves worker safety, enhances automated inspection systems, and facilitates real-time computer vision applications operating under difficult environmental conditions.

6. Algorithm

The proposed Underground Image Quality Enhancement framework employs an **Advanced Retinex-Guided Attention Neural Network** for improving the visibility of underground images captured under poor illumination conditions. Initially, the degraded image undergoes

preprocessing to remove inconsistencies and normalize intensity values. The Retinex decomposition module separates the input image into **illumination** and **reflectance** components. The illumination branch corrects non-uniform lighting, while the reflectance branch suppresses noise and preserves texture details. Multi-scale convolutional layers extract hierarchical image features, and residual learning enables efficient optimization of deep network parameters. Channel attention and spatial attention modules further enhance important structures such as tunnel walls, workers, machinery, and obstacles. Finally, the optimized illumination and reflectance components are fused to reconstruct the enhanced image. The enhanced output is evaluated using image quality metrics and downstream object detection performance.

Let the degraded underground image be represented as

I(x,y)=R(x,y)×L(x,y)I(x,y)=R(x,y)\times L(x,y)I(x,y)=R(x,y)×L(x,y)

where I(x,y)I(x,y)I(x,y) is the observed image, R(x,y)R(x,y)R(x,y) represents the reflectance component containing structural information, and L(x,y)L(x,y)L(x,y) denotes the illumination component.

The enhanced image is reconstructed as

Ienh=R′×L′I_{enh}=R'\times L'Ienh=R′×L′

where R′R'R′ and L′L'L′ represent the optimized reflectance and illumination estimated by the neural network.

The Structural Similarity Index (SSIM) used to evaluate enhancement quality is

SSIM(x,y)=(2μxμy+C1)(2σxy+C2)(μx2+μy2+C1)(σx2+σy2+C2)SSIM(x,y)=\frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}SSIM(x,y)=(μx2+μy2+C1)(σx2+σy2+C2)(2μxμy+C1)(2σxy+C2)

where μ\muμ denotes the mean intensity, σ\sigmaσ represents variance, and σxy\sigma_{xy}σxy is the covariance between the reference and enhanced images.

The Peak Signal-to-Noise Ratio (PSNR) is computed as

PSNR=10log⁡10(MAX2MSE)PSNR=10\log_{10}\left(\frac{MAX^2}{MSE}\right)PSNR=10log10(MSEMAX2)

where MAXMAXMAX is the maximum pixel intensity and MSEMSEMSE represents the Mean Squared Error between the reference and enhanced images. Higher PSNR and SSIM values indicate superior enhancement quality and better preservation of image structures.

7. Modules

Image Acquisition Module

The Image Acquisition Module collects underground images from surveillance cameras, mining robots, drones, vehicle-mounted cameras, and publicly available datasets. The collected images include various underground scenes such as tunnels, mining equipment, workers, conveyor systems, rock formations, and structural components captured under different lighting and environmental conditions. These images form the input dataset for neural network training and evaluation.

Image Preprocessing Module

The Image Preprocessing Module improves image quality before neural network training by performing resizing, normalization, colour correction, denoising, and contrast adjustment. Data augmentation techniques including rotation, scaling, flipping, cropping, and brightness variation increase dataset diversity and improve the robustness of the enhancement model. These preprocessing operations reduce overfitting and improve generalization across different underground environments.

Image Enhancement Module

The Image Enhancement Module employs the proposed Retinex-guided attention neural network to enhance degraded underground images. The module estimates illumination and reflectance separately, extracts multi-scale features using convolutional layers, applies residual learning for stable optimization, and utilizes attention mechanisms to preserve important structures while suppressing background noise. The reconstructed image exhibits improved brightness, visibility, colour consistency, and structural detail.

Quality Assessment Module

The Quality Assessment Module evaluates enhancement performance using objective image quality metrics including PSNR, SSIM, NIQE, entropy, and processing time. Comparative evaluation against conventional enhancement algorithms is also performed to verify the superiority of the proposed framework. These metrics provide quantitative evidence regarding brightness improvement, detail preservation, and overall enhancement quality.

Visualization and Decision Support Module

The Visualization and Decision Support Module presents the original and enhanced images together with quality evaluation metrics through an interactive interface. The enhanced images are additionally supplied to an object detection model to demonstrate improved worker detection, equipment recognition, and obstacle identification. The visualization dashboard assists mining operators, engineers, and safety personnel in monitoring underground conditions more effectively, supporting timely decision-making and improving operational safety.

8. Results and Discussion

The proposed Underground Image Quality Enhancement framework was evaluated using underground image datasets collected from mining environments, tunnel surveillance systems, and publicly available low-light image repositories. The dataset contained images captured under various adverse conditions including poor illumination, dust, haze, uneven lighting, sensor noise, and motion blur. Before model training, the images underwent preprocessing through resizing, normalization, colour correction, denoising, and data augmentation using image rotation, horizontal flipping, brightness variation, and scaling. The proposed neural network was compared with conventional enhancement techniques such as Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma Correction, Retinex-based enhancement, and Zero-DCE. Performance evaluation was conducted using Peak Signal-

to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Natural Image Quality Evaluator (NIQE), entropy, and processing time.

Experimental results demonstrated that the proposed neural network significantly improved the visual quality of underground images compared with traditional enhancement methods. The enhanced images exhibited better brightness distribution, higher contrast, improved colour consistency, reduced sensor noise, and clearer structural details. The Retinex decomposition module effectively corrected non-uniform illumination while preserving reflectance information, resulting in natural-looking enhanced images. Multi-scale convolution enabled the model to recover both fine textures and large structural features, whereas attention mechanisms successfully highlighted important underground objects such as workers, machinery, conveyor belts, tunnel walls, and safety equipment. Compared with conventional enhancement techniques, the proposed framework achieved higher PSNR and SSIM values while producing lower NIQE scores, indicating superior perceptual quality.

The enhanced images also improved the performance of downstream computer vision applications. When supplied to a YOLO-based object detection model, the enhanced images produced higher worker detection accuracy and more reliable identification of mining equipment and underground obstacles than the original degraded images. Detection confidence increased because the enhancement model restored visibility in dark regions while preserving object boundaries and minimizing visual artifacts. The reduction of sensor noise further improved feature extraction by the object detection network. These results demonstrate that the proposed enhancement framework not only improves visual appearance but also increases the effectiveness of intelligent underground monitoring systems.

Overall, the proposed framework provides an efficient solution for underground image enhancement by simultaneously improving illumination, suppressing noise, preserving texture details, and enhancing structural visibility. The integration of Retinex decomposition, residual learning, multi-scale feature extraction, and attention mechanisms enables robust performance under complex underground conditions. The developed system supports intelligent mining operations, infrastructure inspection, worker safety monitoring, autonomous navigation, and emergency response by providing high-quality visual information suitable for both human observation and automated computer vision analysis.

9. Implementation

The proposed Underground Image Quality Enhancement system was implemented using Python because of its extensive support for deep learning and computer vision applications. The development environment consisted of Visual Studio Code and Jupyter Notebook. Image preprocessing operations including resizing, normalization, colour conversion, denoising, and augmentation were performed using OpenCV, NumPy, and Albumentations. The proposed neural network was implemented using the PyTorch framework because of its flexibility in developing deep convolutional architectures. Training and optimization were performed using GPU acceleration to reduce computational time, while Matplotlib was used to visualize training

curves, enhanced images, and performance metrics. Publicly available underground image datasets together with custom mining surveillance images were utilized for model training and evaluation.

The implementation process began by collecting underground images and preparing corresponding training datasets. Image preprocessing improved dataset quality before training the Retinex-guided attention neural network. During training, the network optimized multiple objective functions including reconstruction loss, structural similarity loss, illumination smoothness loss, and perceptual loss. After training, the model enhanced new underground images in real time by estimating optimized illumination and reflectance components before reconstructing the final enhanced image. Performance evaluation was conducted using PSNR, SSIM, NIQE, entropy, and inference time. The enhanced images were also supplied to a YOLO object detection model to evaluate improvements in worker and equipment detection accuracy. Experimental implementation on a computer equipped with an Intel Core i7 processor, 16 GB RAM, NVIDIA RTX GPU, and Windows operating system confirmed that the proposed framework efficiently enhanced underground images while maintaining practical processing speed suitable for intelligent mining and tunnel monitoring systems.

10. Conclusion

This paper presented an **Advanced Neural Network-based Underground Image Quality Enhancement framework** for improving the visibility of images captured under challenging underground conditions. The proposed framework integrates Retinex decomposition, multi-scale convolution, residual learning, and attention mechanisms to simultaneously correct non-uniform illumination, suppress sensor noise, preserve structural details, and restore natural colour appearance. Comprehensive preprocessing techniques, including normalization, denoising, and data augmentation, improved dataset quality and enhanced the robustness of the neural network. The proposed architecture effectively learned complex relationships between degraded underground images and their enhanced counterparts, enabling superior image restoration under low-light and dusty environments.

Experimental evaluation demonstrated that the proposed framework outperformed conventional enhancement techniques such as Histogram Equalization, CLAHE, Gamma Correction, Retinex-based methods, and Zero-DCE in terms of PSNR, SSIM, NIQE, and visual quality. The enhanced images exhibited improved brightness, higher contrast, reduced noise, better texture preservation, and more accurate representation of underground structures. Furthermore, enhanced images significantly improved the performance of downstream computer vision tasks including worker detection, machinery recognition, and obstacle identification. These findings indicate that image enhancement serves not only as a visual improvement technique but also as an essential preprocessing stage for intelligent underground monitoring systems.

Future research may focus on integrating Vision Transformers, diffusion models, Generative Adversarial Networks (GANs), and self-supervised learning techniques to further improve enhancement quality under extremely challenging underground conditions. The incorporation of

Explainable Artificial Intelligence (XAI) may also provide greater transparency regarding neural network decisions, increasing user confidence in safety-critical applications. In addition, deploying lightweight neural architectures on embedded edge devices, autonomous robots, and UAVs can facilitate real-time underground monitoring without requiring high computational resources. Overall, the proposed Underground Image Quality Enhancement framework provides an efficient, scalable, and practical solution for intelligent mining, tunnel inspection, underground infrastructure monitoring, and smart industrial safety applications.

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