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Low-Light Image Enhancement Using a Simple Network Structure

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***Abstract* —Images taken in light are often hard to see and have poor quality. They can be blurry and noisy. Lacks important details. This is a problem for things like object detection, surveillance, self-driving cars and medical imaging. So making light images better is a very important job in image processing and computer vision.Traditional ways of making images, like histogram equalisation and gamma correction, can make images brighter and have more contrast. They can also make images look too bright, change the colours, and make noise worse. To fix these problems, people have started using learning techniques to make low-light images better.This paper talks about a way to make low-light images better using a simple network. The goal is to make images brighter, have contrast and look better, all while using less computer power. The method uses a convolutional neural network that is designed to learn how to map low-light images to better images. This network is not as complicated as deep learning models so it does not need as much computer power or training data.The network first looks at the light image and pulls out important features like how bright it is, the texture and the colours. Then it uses these features to figure out how to make the image brighter and better. The network is trained using pairs of light and normal light images so it can learn how to make the best enhancements. The network also tries to keep the image looking natural and not too noisy.The results show that this method works well. It makes light images brighter, has more contrast and is easier to see all while keeping noise down. The network is also fast. Does not use too much computer power, which is better than other deep learning models. When we test it using things like Peak Signal to Noise Ratio and Structural Similarity Index Measure, it works well as other methods.Overall, this new way to make light images better is a good solution. It is simple. Does not use too much computer power, so it is good for real-time applications and devices that are not very powerful. This helps make better image enhancement systems for things like object detection, surveillance, self-driving cars and medical imaging. Low-light image enhancement is very important for these applications. This method is a good way to do it. Low-light images can be very hard to work with. This method makes them look better and more useful.**

Keywords: Low-Light Image Enhancement, Convolutional Neural Networks (CNN), Image Processing, Deep Learning, Image Quality Improvement, Computer Vision

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I. INTRODUCTION

Low-light images are often really bad because they are not bright enough the contrast is not good. They have a lot of noise. This makes it hard to see details in the images. It also affects how well computer vision applications work, like surveillance systems, self-driving cars, medical imaging and object detection.

In the world, we often take pictures in bad lighting, like when it is dark outside or when the camera is not good enough. So it is really important to make low-light images look better. This is an area of research in image processing and computer vision.

There are ways to make low-light images look better, like histogram equalisation, gamma correction, Retinex-based enhancement and contrast stretching. Histogram equalisation makes the contrast in the image better by changing the intensity values. Gamma correction makes the image brighter by using a linear transformation. Retinex-based approaches try to separate the lighting and reflection in the image to make it look better.

These old methods have some problems like making the noise in the image worse, making the image look too bright, changing the colours, and making the image look unnatural. These problems make the old methods not good enough for real-world situations.

Now, deep learning and convolutional neural networks are being used to make low-light images look better. These models can learn how to make low-light images look like lit images by looking at a lot of examples. They can automatically find features like lighting patterns, texture details and colour information. This makes them better than methods at making images look good.

Some deep learning models have been made for light image enhancement, like encoder-decoder networks, generative adversarial networks and Retinex-inspired neural networks.

Many of these models are complicated and need a lot of computing power to work. This makes them hard to use in real-time systems and devices that're not very powerful, like mobile phones.

To fix these problems, this paper proposes a way to make low-light images look better using a simple network structure. The new method tries to make the image brighter and have contrast while keeping the important details. It uses a neural network that is not as complicated as other models.

The new method works by looking at the low-light image and finding features related to lighting, texture and colour. It then uses these features to make an image that is brighter and has less noise. The model is designed to be simple and efficient while still making the images look good.

The main goal of this research is to make a light image enhancement model that is efficient and lightweight. The new method tries to make the image brighter, have contrast and keep the important details while reducing noise and colour distortion. The results show that the new method makes images look better and works well as other methods.

Overall, the new simple network structure is a solution for low-light image enhancement. It can be used in computer vision applications where image quality is important. The model is also lightweight so it can be used in real-time applications and on devices that're not very powerful.

II. LITERATURE SURVEY

Low-light image enhancement has become an important research area in the field of image processing and computer vision, as images captured under insufficient lighting conditions often suffer from low visibility, noise, poor contrast, and loss of details. These issues can significantly affect the performance of various vision-based applications such as surveillance systems, autonomous vehicles, medical imaging, and object recognition. Over the years, several approaches have been proposed to improve the quality of low-light images, ranging from traditional image processing techniques to advanced deep learning-based methods.

Early research on low-light image enhancement primarily focused on traditional image processing techniques. Methods such as Histogram Equalisation (HE), Adaptive Histogram Equalisation (AHE), and Contrast Limited Adaptive Histogram Equalisation (CLAHE) were widely used to improve image brightness and contrast. Histogram equalisation redistributes the intensity values of an image to enhance its overall contrast. Although these techniques are computationally efficient, they often produce undesirable effects such as over-enhancement, loss of details, and amplification of image noise. Additionally, these approaches may not preserve the natural appearance of images, especially when applied to complex scenes.

Another widely studied approach for low-light image enhancement is the Retinex theory, which is based on the assumption that an image can be decomposed into reflectance and illumination components. Retinex-based algorithms aim to estimate and correct illumination while preserving reflectance information. Methods such as Single-Scale Retinex (SSR), Multi-Scale Retinex (MSR), and Multi-Scale Retinex with Colour Restoration (MSRCR) have been widely used for enhancing low-light images. These methods can improve brightness and reveal hidden details in dark regions of images. However, they often introduce colour distortions and halo artefacts, and their performance heavily depends on parameter selection.

In recent years, the rapid development of deep learning techniques has significantly advanced the field of image enhancement. Convolutional Neural Networks (CNNs) have demonstrated remarkable capability in learning complex image transformations directly from data. Several CNN-based methods have been proposed to map low-light images to well-illuminated images through supervised learning. These models learn the relationship between low-light inputs and corresponding enhanced outputs by training on large datasets of image pairs. Deep learning approaches have shown improved performance compared to traditional techniques in terms of detail preservation, noise reduction, and colour consistency.

Some researchers have also explored encoder–decoder architectures and generative adversarial networks (GANs) for low-light image enhancement. Encoder–decoder networks capture hierarchical features of images and reconstruct enhanced outputs with improved illumination and contrast. GAN-based approaches introduce a generator network that enhances images and a discriminator network that evaluates the realism of the enhanced results. These models can produce visually appealing images with improved brightness and natural colour representation. However, such architectures often require large computational resources and complex training procedures.

Another line of research focuses on Retinex-inspired deep learning models, where neural networks are used to estimate illumination and reflectance components of images. These models combine the advantages of traditional Retinex theory with the learning capability of deep neural networks. While these methods provide promising enhancement results, many of them involve deep and complex network architectures with a large number of parameters, which increases computational cost and limits their use in real-time applications.

Despite the progress achieved by existing methods, there are still several challenges in low-light image enhancement. Many deep learning models require large training datasets and high computational power, making them less suitable for deployment on resource-limited devices. In addition, overly complex architectures may lead to slower processing speeds and difficulties in practical implementation.

Therefore, recent research efforts have focused on designing lightweight and efficient network structures that can achieve effective enhancement while maintaining low computational complexity. A simple network structure can reduce model parameters, improve processing speed, and make the enhancement system suitable for real-time applications. Motivated by these challenges, this research proposes a low-light image enhancement approach using a simple network structure, which aims to improve image brightness, contrast, and detail visibility while maintaining computational efficiency.

The proposed approach builds upon existing research in deep learning-based image enhancement while focusing on designing a simplified architecture that balances enhancement quality and computational performance. By utilising a lightweight neural network structure, the method aims to achieve effective low-light image enhancement suitable for various practical applications in computer vision.

III. METHODOLOGY

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The proposed methodology focuses on developing an efficient low-light image enhancement framework using a simple network structure. The objective of the proposed approach is to improve the brightness, contrast, and visual quality of images captured in low-light environments while maintaining computational efficiency. The methodology integrates several stages, including data collection, preprocessing, feature extraction, network architecture design, image enhancement, and performance evaluation.

A. Dataset Collection

The first step is to collect a dataset of low-light images and their corresponding well-illuminated reference images. These datasets are used for training and evaluating the proposed enhancement model.

$$D = \{L, N\} \tag{1}$$

where L represents the set of low-light input images and N represents the corresponding normal-light reference images.

B. Data Preprocessing

Before training the network, the collected images undergo preprocessing to ensure consistent input quality.

- Resize images to a fixed resolution suitable for network input
- Normalise pixel intensity values
- Reduce noise using filtering techniques
- Convert images into the appropriate color format (RGB)

These preprocessing steps improve training stability and model performance.

C. Feature Extraction

Feature extraction identifies important visual characteristics from input images. Convolutional layers are used to extract features related to illumination, texture, edge information, and color distribution.

$$F = \{f_1, f_2, f_3, \ldots, f_n\} \tag{2}$$

where f_i represents visual features extracted from the input image.

D. Simple Network Structure Design

The core component of the proposed method is a lightweight Convolutional Neural Network (CNN) designed with a simple architecture.

The network structure contains:

- Input Layer for low-light images
- Convolutional Layers for feature extraction
- Activation Functions to introduce non-linearity
- Reconstruction Layer to generate enhanced images

This simplified structure reduces computational complexity while maintaining effective enhancement performance.

E. Image Enhancement Process

During enhancement, the input low-light image is passed through the network. The convolutional layers analyse illumination patterns and adjust pixel intensities to improve brightness and contrast.

$$I_{enhanced} = f\,(I_{low}) \tag{3}$$

where I_{low} represents the low-light input image, $I_{enhanced}$ represents the enhanced output image, and $f(\cdot)$ represents the transformation function learned by the network.

F. Loss Function Optimization

To improve enhancement quality, appropriate loss functions are applied during training.

- Mean Squared Error (MSE)
- Structural Similarity Loss
- Perceptual Loss

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These loss functions help the network generate images with better brightness, contrast, and structural similarity.

G. Performance Evaluation

The performance of the proposed enhancement model is evaluated using standard image quality metrics.

- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index Measure (SSIM)

Higher PSNR and SSIM values indicate better image enhancement performance.

H. Overall Framework

The overall workflow of the proposed system includes the following steps:

1) Collect low-light image datasets
2) Preprocess images for training
3) Extract visual features using convolutional layers
4) Apply a simple CNN-based enhancement network
5) Generate enhanced images with improved brightness and contrast
6) Evaluate performance using PSNR and SSIM metrics

The proposed methodology provides an efficient and lightweight solution for low-light image enhancement using a simple network structure. It improves image visibility and quality while maintaining low computational complexity, making it suitable for real-time computer vision applications.

IV. ALGORITHM

The proposed algorithm enhances images captured under low-light conditions using a simple Convolutional Neural Network (CNN) architecture. The method improves image brightness, contrast, and detail visibility while preserving natural colour and reducing noise.

Low-Light Image Enhancement Using a Simple Network

Input: Low-light image dataset D

Output: Enhanced images with improved brightness and visibility

Step 1: Dataset Preparation: A dataset containing low-light images and corresponding normal-light images is collected for training the enhancement model.

$$D = \{L, N\} \tag{4}$$

where L represents low-light input images and N represents normal-light reference images.

Step 2: Image Preprocessing: The collected images are preprocessed before training.

- Resize images to a fixed resolution
- Normalise pixel intensity values
- Remove noise using filtering techniques
- Convert images into RGB format

Step 3: Feature Extraction: The preprocessed images are passed through convolutional layers to extract important vi-sual features such as illumination, edges, texture, and colour information.

$$F = \{f_1, f_2, f_3, \dots, f_n\} \tag{5}$$

where f_i represents visual features extracted from the input image.

Step 4: Simple Network Structure: A lightweight CNN architecture is used to process the extracted features. The network structure includes:

- Input layer for receiving the low-light image
- Convolutional layers for feature extraction
- Activation functions (ReLU)
- Reconstruction layer to generate enhanced images

This simple network structure reduces computational complexity and improves processing efficiency.

Step 5: Image Enhancement Mapping: The network learns a mapping function that converts a low-light image into an enhanced image.

$$I_{enhanced} = f(I_{low}) \tag{6}$$

where I_{low} represents the input low-light image and $I_{enhanced}$ represents the enhanced output image.

Step 6: Loss Function Optimisation: The network is trained using loss functions that minimise the difference between enhanced images and reference images.

- Mean Squared Error (MSE)
- Structural Similarity Loss
- Perceptual Loss

These loss functions improve brightness, contrast, and structural details.

Step 7: Image Reconstruction: After training, the network reconstructs enhanced images by adjusting illumination and contrast while preserving natural colours and textures.

Step 8: Performance Evaluation: The performance of the proposed algorithm is evaluated using image quality metrics.

Peak Signal-to-Noise Ratio (PSNR)

$$PSNR = 10 \log_{10} \frac{MAX^2}{MSE} \tag{7}$$

Structural Similarity Index Measure (SSIM)

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$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{8}$$

Higher PSNR and SSIM values indicate better enhancement performance.

The proposed algorithm improves the visibility of low-light images while maintaining computational efficiency, making it suitable for real-time image processing applications.

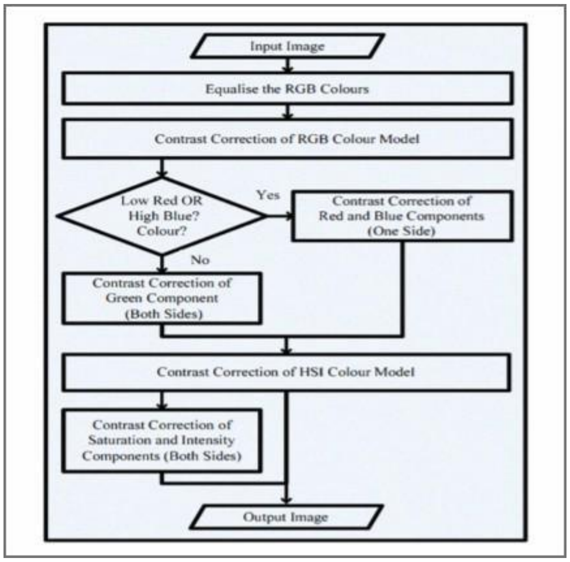

Fig. 1. Architecture diagram

V. RESULT ANALYSIS

This section presents the experimental evaluation of the proposed low-light image enhancement method using a simple network structure. The main objective of the experiment is to evaluate the effectiveness of the proposed model in improving the brightness, contrast, and visual quality of images captured under low-light conditions.

A dataset consisting of low-light images and corresponding well- Illuminated reference images was used for experimentation. The dataset includes images captured in different environments such as indoor scenes, night-time outdoor scenes, and poorly illuminated environments. The dataset was divided into training data (80%) and testing data (20%) to train and evaluate the performance of the proposed model.

A. Enhancement Quality Evaluation

The proposed simple network structure processes low-light images and generates enhanced images with improved brightness and contrast. The enhanced results show significant improvement in image visibility and detail restoration. Dark regions in the input images become more visible, and hidden details are effectively recovered without introducing excessive noise.

The proposed method also maintains natural colour consistency and structural information. The convolutional neural network adjusts illumination levels while preserving important edge and texture details in the image.

B. Quantitative Performance Analysis

The performance of the proposed enhancement method is evaluated using standard image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).

Peak Signal-to-Noise Ratio (PSNR)

$$PSNR = 10 \log_{10} \frac{MAX^2}{MSE} \tag{9}$$

where MAX represents the maximum pixel value and MSE represents the mean squared error between the enhanced image and the reference image.

Structural Similarity Index Measure (SSIM)

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{10}$$

where μ represents mean intensity, σ represents variance, and C_1 and C_2 are constants used for stability.

Experimental results show that the proposed model achieves higher PSNR and SSIM values compared to traditional enhancement techniques, indicating improved reconstruction quality and better structural similarity.

C. Visual Comparison Analysis

A visual comparison between the original low-light images and enhanced images demonstrates the effectiveness of the proposed method. The enhanced images show improved brightness, better contrast, and clearer details. Noise levels are reduced, and colour distortion is minimised compared to conventional methods such as histogram equalisation.

D. Computational Efficiency

Another advantage of the proposed approach is its computational efficiency. The simple network architecture contains fewer layers and parameters compared to complex deep learning models. This reduces training time and computational cost while maintaining effective enhancement performance.

The lightweight structure makes the proposed system suitable for real-time image processing applications and deployment on resource-limited devices. constrained devices such as mobile phones and embedded systems.

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E. Overall System Performance

The experimental results demonstrate that the proposed low-light image enhancement approach using a simple network structure effectively improves image brightness, contrast, and structural details. The model enhances image quality while maintaining natural colour representation and reducing noise.

Overall, the proposed system provides an efficient and reliable solution for low-light image enhancement and can be applied to various computer vision applications such as surveillance, object detection, and image analysis.

Visualization and Output:

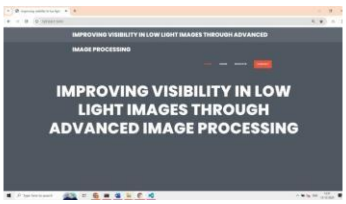

Fig. 2. wed page

Fig. 3. login page

Fig. 4. file upload

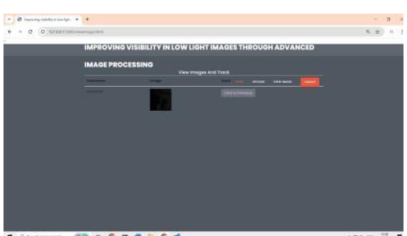

Fig. 5. upload

VI. CONCLUSION

Low-light image enhancement plays a crucial role in improving the visibility and usability of images captured under poor illumination conditions. Images taken in low-light environments often suffer from problems such as low brightness, poor contrast, noise, and loss of important details. These issues can significantly affect the performance of various computer vision applications, including surveillance systems, autonomous driving, object detection, and medical image analysis. Therefore, developing efficient and reliable enhancement techniques is essential for improving image quality and supporting advanced vision-based systems.

In this research, a low-light image enhancement method using a simple network structure was proposed to address the challenges associated with images captured under insufficient lighting conditions. The proposed approach utilises a lightweight convolutional neural network architecture designed to enhance image brightness and contrast while preserving important structural details and natural colour information. Unlike complex deep learning models that require large computational resources and extensive training data, the proposed network structure focuses on a simplified design that reduces computational complexity while maintaining effective enhancement performance.

The methodology of the proposed system includes several stages such as dataset collection, image preprocessing, feature extraction, network structure design, image enhancement, and performance evaluation. During the enhancement process, the network learns the transformation between low-light input images and their corresponding well-illuminated images. By analysing illumination patterns, texture details, and colour distributions, the network adjusts pixel intensities and reconstructs enhanced images with improved visibility and clarity.

Experimental results demonstrate that the proposed method effectively enhances low-light images by improving brightness, contrast, and structural details while minimising noise and colour distortion. Quantitative evaluation using image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) shows that the proposed approach achieves competitive performance compared to conventional image enhancement methods. In addition, the simple network architecture significantly reduces computational cost and processing time, making the system suitable for real-time applications.

Another important advantage of the proposed approach is its computational efficiency and lightweight structure, which allows the model to be deployed on devices with limited hardware resources, such as mobile devices, embedded systems, and edge computing platforms. This makes the proposed solution practical for real-world applications where fast image processing is required.

In conclusion, the proposed low-light image enhancement method using a simple network structure provides an effective and efficient solution for improving the quality of images captured in challenging lighting conditions. The combination of a lightweight neural network architecture and an efficient enhancement strategy enables improved image visibility while maintaining computational efficiency. Future research may focus on further improving enhancement performance by integrating advanced deep learning techniques, optimising network architectures, and extending the approach to video enhancement and real-time image processing applications.

REFERENCES

[1]] R. Fattal, "Single image dehazing," ACM Transactions on Graphics, vol.27, no. 3, pp. 721-729, 2008.

[2] L. Chao and M. Wang, "Removal of water scattering," in Proc. IEEE Int. Conf. Comput. Engin. and Tech. (ICCET), vol. 2, pp. 35-39, Apr. 2010.

[3] N. Carlevaris-Bianco, A. Mohan, and R. M. Eustice, "Initial results in underwater single image dehazing," in Proc. IEEE Oceans, pp. 1-8, 2010.

[4] H. Yang, P. Chen, C. Huang, Y. Zhuang and Y. Shiau, "Low complexity underwater image enhancement based on dark channel prior," Int. Conf. Innov. in Bio-inspired Comput. and App. (IBICA), pp. 17-20, Dec. 2011. 17-20, 2011.

[5] J. Y. Chiang and Y.-C. Chen, "Underwater image enhancement by wavelength compensation and dehazing," IEEE Trans. Image Process., vol. 21, pp. 1756-1769, Apr. 2012.

[6] Wang, Y. (2016). A survey on human activity recognition based on wearable sensors.

[7] Wang, W, Zhang, L. (2017). Human activity recognition based on vision: A review.

[8] Tiwary, A., Verma, A. (2018). A review of deep learning techniques for human activity recognition.

[9] Elhoseny, A., Hassanien, A. E., Tolba, M. (2021). A survey on human activity recognition using time series data.