International Journal of Advances in Electrical Engineering 2024; 5(1): 10-14

International Journal of Advances in Electrical Engineering

E-ISSN: 2708-4582
P-ISSN: 2708-4574
IJAEE 2024; 5(1): 10-14

www.electricaltechjournal.com
Received: 08-11-2023
Accepted: 13-12-2023

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Image enhancement using CNN

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DOI: https://doi.org/10.22271/27084574.2024.v5.i1a.47

Abstract
This study explores Image Enhancement using CNN experiments conducted using the LOL dataset has the potential to greatly increase the quality of photographs taken in low light. It has been demonstrated that CNN-based low-light picture enhancement techniques perform better than conventional techniques in terms of both quantitative and qualitative criteria. CNNs are excellent for enhancing images in low light because they can discover intricate correlations between picture data. A CNN is usually trained on a dataset of paired low-light and improved pictures as part of CNN-based low-light image improvement techniques. CNN gains the ability to create improved images that resemble the ground truth images in the dataset by extracting characteristics from photos taken in low light. There are several benefits that CNN-based low-light picture enhancing techniques offer over conventional techniques. First, CNNs perform better than conventional techniques because they can understand intricate correlations between visual data. Secondly, fresh low-light pictures can be improved using CNN-based techniques without requiring paired training data. They become more useful and broadly applicable as a result. Third, improved photographs appear more realistic and natural because CNN-based techniques may retain semantic information in low-light photos.

Keywords: Deep learning, convolutional neural network (CNN), LOL dataset

Introduction
Pictures have an impact, on our lives acting as a powerful tool for communication and storing information. However the quality of pictures can often suffer due to factors like lighting, noise or limitations in the cameras abilities. Enhancing images is a field in computer vision and image processing that aims to improve their quality while preserving crucial details and information. [1]

Traditional techniques for enhancing images have relied on designed algorithms and filters which often struggle to produce high quality results across various situations. In years Convolutional Neural Networks (CNNs) have emerged as a game changing technology in image enhancement. [2] They offer a data driven approach to the problem by learning patterns and features from datasets. CNNs have showcased capabilities in tasks like image classification, object detection and segmentation making them adaptable, for enhancing images. [3]

Image enhancement using Convolutional Neural Networks (CNNs) represents a groundbreaking approach in the field of computer vision and image processing. Images are pivotal in various domains, including surveillance, medical imaging, photography, and more. However, poor lighting conditions, noise, and sensor limitations can often degrade image quality. [4]

CNNs bring several advantages to image enhancement. Firstly, they excel at feature learning, automatically extracting hierarchical features from raw pixel data. This feature learning capability enables them to capture intricate patterns, textures, and structures within images, facilitating the enhancement of relevant aspects like edges, textures, and object contours. Secondly, CNNs are remarkably adaptable to diverse scenarios. [5] Unlike traditional methods that often require manual parameter adjustments or specific tuning, CNN-based models can enhance images under various lighting conditions, weather situations, or with different camera sensors without human intervention. [6]

Understanding CNN Architecture
Convolutional Neural Networks (CNNs) can be pivotal for grasping their significance in modern computer vision and image processing.

CNNs are a class of deep learning models specifically designed to process grid-like data, such as images and videos. [7] They are inspired by the visual processing that occurs in the human brain, where neurons respond to stimuli only in specific receptive fields, allowing for the recognition of patterns and shapes in visual input. [8]

At the core of CNNs are convolutional layers, which apply a set of learnable filters (kernels) to the input image. These filters slide across the input, capturing local features and creating feature maps. The filters are learned through the training process, allowing the network to automatically identify and extract relevant features from the input data. This feature extraction capability is critical in tasks like image classification, object detection, and image enhancement. [9]

CNNs also incorporate pooling layers that down sample the feature maps, reducing the spatial dimensions while preserving important features. [10] Pooling helps in creating a hierarchical representation of the input, enabling the network to capture both low-level details and high-level abstractions. The combination of convolutional and pooling layers allows CNNs to learn and represent complex patterns within images efficiently. [14]

One of the key advantages of CNNs is their ability to learn hierarchical features. In deeper layers of the network, neurons respond to more complex and abstract features, such as object parts or entire objects. This hierarchical representation is what makes CNNs particularly effective in image recognition tasks, as they can learn to recognize objects at various levels of granularity. [15]

Furthermore, CNNs often include fully connected layers at the end of the architecture to perform classification or regression tasks based on the extracted features. These layers aggregate information from the previous layers to make final predictions. [16]

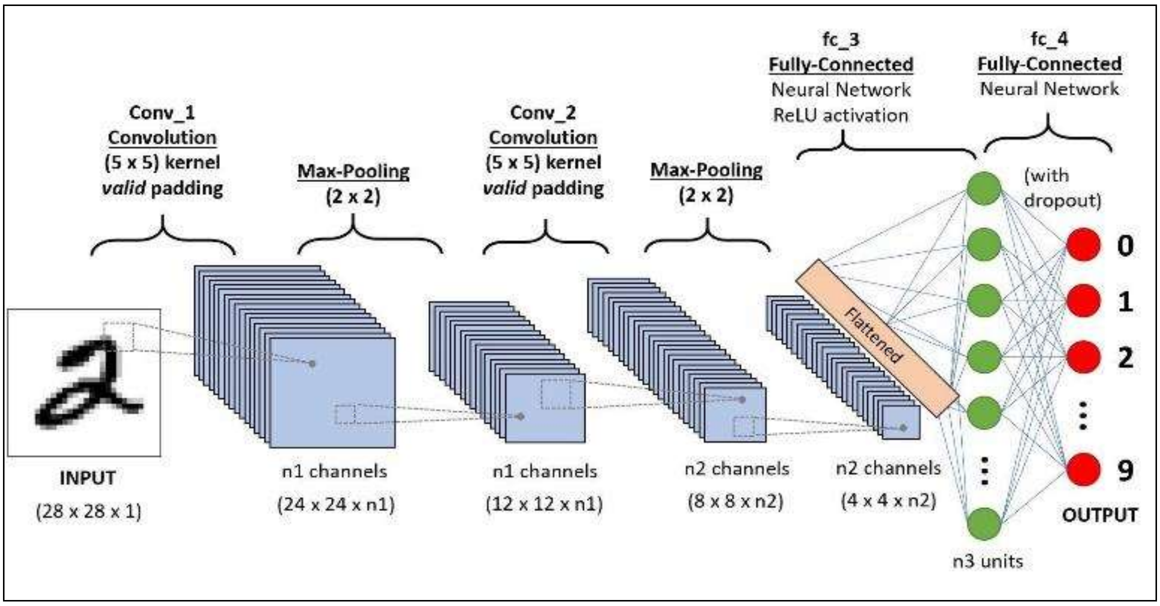

Fig 1: CNN Architecture

Role of Deep Learning in Object Recognition

Deep learning, particularly through Convolutional Neural Networks (CNNs), has significantly reshaped the landscape of image enhancement by offering powerful tools capable of improving image quality across various domains and challenges. [11] CNNs excel in this domain due to their innate capacity to learn intricate representations and patterns from data, directly impacting the quality of enhanced images. The fundamental strength of CNNs lies in their ability to autonomously learn hierarchical features from raw image data without explicit human intervention. Through multiple layers comprising convolutions, pooling, and activation functions, CNNs progressively extract and encode complex features, allowing for the understanding and representation of vital elements within images. [12]

A pivotal aspect contributing to CNNs' efficacy in image enhancement is their adaptability and capacity for generalization. These networks can learn from diverse datasets with varying image qualities, lighting conditions, and contexts. [13] Consequently, CNNs can generalize their learned representations, enabling them to enhance images in scenarios not explicitly encountered during training. This adaptability is crucial in real-world applications where images may exhibit diverse attributes, ensuring CNN-based enhancement techniques remain versatile and effective across a range of conditions. [17]

The inherent capability of CNN architectures to model intricate relationships between input and output is instrumental in image enhancement tasks. By understanding the complex dependencies between low-quality images and their desired high-quality versions, CNNs can effectively restore missing details, reduce noise, and enhance overall image quality. [18] This ability to capture and reconstruct relevant image features facilitates the generation of visually improved outputs, significantly benefiting applications reliant on high-quality image data. [19]

Furthermore, CNNs facilitate an end-to-end learning approach, allowing the network to learn the mapping directly from low-quality input images to high-quality output images. This streamlined learning process eliminates the need for intermediate manual steps, enabling the network to generate enhanced images based on learned patterns and features. [20] This aspect streamlines the enhancement pipeline, potentially improving efficiency and effectiveness in producing high-quality image outputs.

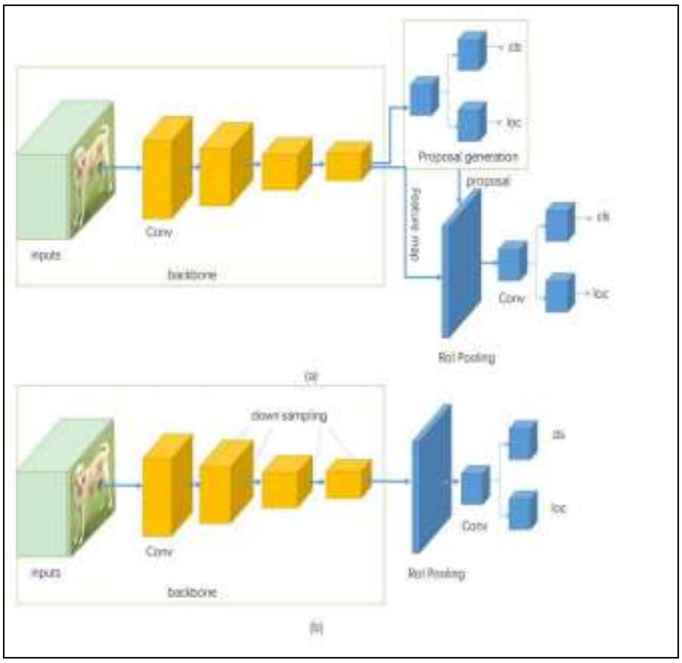

Fig 2: Role of deep learning

Literature Survey

Traditional image enhancement methods often encounter limitations when dealing with real-world images that exhibit diverse lighting conditions and complex content. Techniques like histogram equalization, contrast stretching, and spatial filtering have been used extensively, but they lack the adaptability and learning capabilities that are inherent to CNNs. One of the primary drawbacks of traditional methods is their reliance on fixed, handcrafted rules and parameters, which may not effectively capture the nuanced characteristics of the images they aim to enhance.

In contrast, the introduction of CNNs into the realm of image enhancement has brought about a paradigm shift. [21] CNN-based image enhancement methods adopt a data-driven approach, leveraging the power of extensive datasets containing pairs of input images and their corresponding enhanced versions. These datasets are integral in training CNN models to learn intricate mappings from raw input images to their desired enhanced outputs. By doing so, CNNs are capable of capturing complex and nonlinear relationships between image features and the desired enhancement effects. [22]

An essential feature of CNN-based image enhancement is the concept of end-to-end learning. [31] In this context, end-to-end learning implies that CNNs are trained to perform the entire image enhancement process seamlessly, from the initial raw input image to the final enhanced output. [22] This eliminates the need for a multitude of handcrafted pre-processing steps or the reliance on domain-specific knowledge. CNNs take on the role of feature extractors, learners, and generators, allowing for a more holistic and adaptive approach to image enhancement. [23, 32]

The training process of CNNs for image enhancement involves the use of loss functions that quantify the disparity between the enhanced output and the ground truth, or reference, images. Common loss functions include mean squared error (MSE), which measures the pixel-wise difference between the enhanced and reference images [24]. In addition to traditional loss functions, perceptual loss metrics have gained prominence. Perceptual loss considers the high-level features extracted from intermediate layers of a pre-trained neural network, allowing the model to focus on perceptually relevant aspects of image quality, such as texture, structure, and content. [25]

Methodology

Image enhancement using Convolutional Neural Networks (*cnns*) encompasses a systematic sequence of steps designed to leverage deep learning for improving image quality. Initially, the process involves gathering and preprocessing a diverse dataset comprising low-quality images and their corresponding high-quality references. These images undergo normalization and resizing to create a clean dataset. Subsequently, the selection of an appropriate CNN architecture suited for image enhancement tasks, like U-Net or *resnet*, becomes pivotal. Determining the architecture's complexity, including layer numbers, filter sizes, and activation functions, aligns with the task's intricacy and computational resources available. [26]

The dataset is partitioned into training, validation, and test sets after the architecture is chosen, guaranteeing balanced distributions under varied lighting conditions or picture quality. The training data is the creation of input-output pairs that associate low-quality photos with their high-quality equivalents. [33] Following the initialization of the CNN with appropriate weights and an iterative optimization process, his data drives the training phase. Stochastic gradient descent or Adam algorithms are used for parameter optimization, and methods like Mean Squared Error (MSE) or perceptual loss are used as guides. [27]

Following the training phase, hyper parameters such as learning rates and batch sizes are fine-tuned with the goal of maximizing network performance while minimizing over fitting. When evaluating the trained CNN, quantitative metrics like as PSNR, SSIM, or MSE are used to evaluate improvements in picture quality. These metrics are supplemented with qualitative evaluations made by comparing the improved images to their originals visually. The improved photos are further refined by post-processing methods like denoising filters or histogram equalization, and the model is optimized for use in real-time applications.

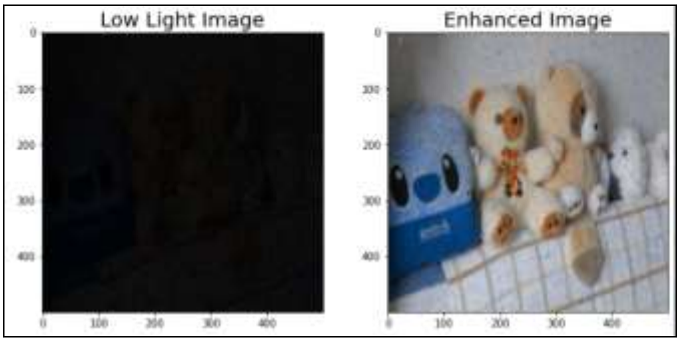

Fig 4: Image enhancement using CNN

Conclusion

In conclusion, the application of Convolutional Neural Networks (CNNs) for image enhancement represents a groundbreaking advancement in computer vision [28]. These techniques leverage deep learning to intelligently improve image quality, addressing challenges such as noise reduction and detail preservation. [29] The success of CNNs in learning intricate image patterns ensures robust performance across diverse datasets, making them accessible and applicable in various real-world scenarios. [30] However, it is crucial to prioritize ethical considerations and responsible deployment. [34] Overall, CNN-based image enhancement signifies a transformative shift, promising superior visual content and paving the way for future innovations in computer vision. [35]

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