Babylonian Journal of Machine Learning
Vol.2024, **pp**. 30–47
DOI: https://doi.org/10.58496/BJML/2024/003; ISSN: 3006–5429
https://mesopotamian.press/journals/index.php/BJML

Research Article

Image Enhancement using Convolution Neural Networks

Hasan Ahmed Salman [1,*], Ali Kalakech [2]

[1] *Computer Science Department, University Arts, Sciences and Technology, Beirut, Lebanon*.

[2] *Computer and Communication Engineering Department, School of Engineering Lebanese International University, Beirut, Lebanon*.

ARTICLE INFO

Article History
Received 29 Oct 2023
Revised 27 Nov 2023
Accepted 10 Dec 2023
Published 25 Jan 2024

Keywords
Machine Learning
Deep Learning
Image Enhancement
CNN

ABSTRACT

The research presents a comprehensive exploration of the topic of image enhancement using convolutional neural networks (CNN).The research goes deeper into the advanced field of image processing based on the use of neural networks to automatically and efficiently improve the quality and detail of images. The thesis shows that convolutional neural networks are one of the types of deep neural networks, which are specially designed to gain knowledge from big data and extract complex features and patterns found in images. The different layers of the grid are discussed in detail, dealing with images incrementally and extracting different attributes in each layer. The research also highlights CNN's ability to detect, learn and improve important details found in images through convolutions, filtering and data aggregation processes. The proposed CNN image enhancement model was developed and tested on both medical and normal images. The images were optimized using the proposed model and compared with other models. Various quality measures were used to evaluate the results. The results showed that the proposed model can significantly improve the quality of images.

1. INTRODUCTION

Image enhancement using convolutional neural networks (CNN) [1] is an advanced field of image processing [1] to automatically and efficiently improve the quality and detail of images [2]. Convolutional neural networks are one of the types of deep neural networks [3], designed specifically for acquiring big data recognition and extracting complex features and patterns found in photographs. When convolutional neural networks are used [1] in image optimization, the network is trained on a set of enhanced images and high-quality images [4], where enhanced images are the target results. During the CNN training process, the Model [5,6] learns how to match internal and external images and extract the patterns and information necessary to improve the image.

1.1 Problem Statement

Image enhancement using convolutional neural networks aims to improve the quality and visual characteristics of the image through the use of deep learning techniques as well as the use of filters for each type of image, whether it is colored or grayscale. The goal is to overcome the limitations of traditional methods and apply complex transformations for enhanced image quality.

A. Key components of the problem statement include:

1. Improve image quality:

Thanks to the ability of CNN to effectively use data and extract features from images, it can improve image quality by increasing its clarity and detail.

2. Improve sharpness:

CNN can help enhance the sharpness and clarity of the image, improving the contrast of the edges and making the image appear sharper.

*Corresponding author. Email: has062@live.aul.edu.lb

3. Improve contrast:

Using CNN, the contrast of the image can be enhanced, which leads to better identification of different areas and improves the power of distinguishing between them.

4. Improve brightness:

CNN can improve the brightness levels of the image, enhancing the visibility of details in low-light areas.

5. Learn complex features:

CNN can capture low-level features, such as edges and corners, as well as understand high-level meanings, which helps in analyzing and comprehensively improving the image.

6. Improve visual attractiveness:

Thanks to the improvement in quality and detail, CNN can contribute to making the image more visually appealing and attractive to the viewer.

B. Objectives/Sub- Sub-Convolutional Neural Networks (CNNs).

For the purpose of designing the CNN architecture to improve the image. These are the most important steps to improve the image are: -

1. Defining the problem and goals:

We define the goals of improving the image and the specific features aimed at improving it, such as sharpness, contrast or color vividness.

2. Input layer:

Select the size of the image we want to optimize the dimensions of the input layer based on the size of the input images. And make sure it absorbs the necessary information to extract an effective advantage.

3. Layers of convolutions:

Use multiple convolutional layers to capture hierarchical features at different levels. Start with the lower-level features (edges and textures) in the early layers and progress to the higher-level features (shapes and patterns) in the deeper layers.

- Experiment with different filter sizes to capture both fine and coarse features.
- Consider using techniques such as batch normalization to improve convergence and organization.

4. Activation functions:

Enable the network to learn complex relationships within the data.

5. Assembly layers:

Integration of Assembly layers to reduce spatial dimensions, reduce computational complexity and increase the receptive field.

6. Fully connected seams:

Depending on the complexity of the task, add one or more fully connected layers at the end of the network to capture global information and create the final output.

7. Output layer:

Design the output layer based on the selected optimization task. To modify the grayscale intensity or multiple color correction neurons.

8. Loss function:

- Select the appropriate loss function that reflects the difference between the real images and the improved image.

9. Improved:

Filter selection to reduce the loss function during the training process. And use different learning rates to find the optimal balance between convergence speed and stability.

10. Organization:

Implementation of organization techniques to prevent overfitting, especially if the form contains a large amount of information.

11. Evaluation of model data:
Split your data set into training and validation groups to monitor the performance of the model during training. Use the scales for image optimization for example (PSNR, SSIM).

12. Confirm the information:
Ensure the values of the various Super-information, (filter sizes, layer depths, learning rates), to improve the performance of the model.

13. Transfer of learning
Take advantage of pre-trained models or transfer learning. We adjust the pre-trained model in the selected image optimization task if we have limited data.

14. Model training:
Such a diverse data set of images that we want. Monitoring the progress of the training and adjusting the information we obtain to the requirements of the improvement or model.

15. And validation:
Evaluation of the model in a separate test group to ensure generalization to new, invisible data. CNN architecture can be systematically designed to improve the image, considering the requirements and goals that have been mentioned above for our work.

1.2 Research questions

How can the CNN training system improve image quality and reduce noise to remove all impurities and repair image damage or high resolution, considering the preservation of the original image content while continuing to achieve visual improvement?

1.3 Importance of research

A. Improve image quality: image enhancement techniques using CNN help improve image quality by increasing clarity and detail and reducing noise and blur. This is useful in a variety of applications such as medical imaging, photography and space photography.
B. Improved analysis and inference: improved images can positively affect the ability of systems to analyze and infer images. For example, in object recognition and medical imaging applications, optimization can increase the accuracy of systems analysis.
C. Image classification optimization: image optimization techniques can be used to improve the quality of images before they are used as training data for CNN networks to classify images. This may contribute to an increase in the accuracy of image classification.
D. Improve medical imaging: in the field of Medicine, image enhancement techniques using CNN can help improve radiology and medical imaging images, contributing to the accurate diagnosis of diseases and health conditions.
E. Increased efficiency of loading and analysis: in communication applications, the quality of sent and received images can be improved using CNN. This reduces bandwidth consumption and increases the speed of loading and analysis.
F. Detail optimization and photo analysis: image optimization can contribute to improving the quality of detail and photo analysis processes, such as converting written texts into editable text.

1.4 Search limitations

A. Available data: the quality of the results may be highly dependent on the quality and variety of the data set used in the training of the model. If the data set is not sufficient or represents a variety of situations, it may hurt the performance of the model.
B. Data volume: training a CNN model on a large data set can be expensive in terms of time and resources. Sometimes, the low volume of data used can lead to overfitting where the model over-learns the details of the training data and does not generalize well to the new data.
C. Complexity and depth: the design of a complex and deep CNN model can lead to an increase in the time spent on training and the required resources. You may need to balance complexity and performance to get good results without unnecessarily increasing complexity.

D. Improve computational capabilities: some advanced operations in image optimization using CNN need high computational capabilities, which means that you may need powerful processing and powerful GPUs to achieve good performance.
E. Interpretation of results: some CNN models may be very complex, making it difficult to understand how to make decisions and manipulate data. Interpreting the results of the model can be challenging, especially if complex layers such as bangs are used.
F. Overcoming image-related issues: image optimization can be a challenge in cases of significant blurring, inappropriate lighting conditions, or poor detail. These challenges can be difficult to overcome and require special algorithms.
G. Hardware and software requirements: you may need a good knowledge of programming, model training techniques and working with libraries such as TensorFlow or Porch.

2. LITERATURE REVIEW

Image optimization techniques can be classified into two main groups: traditional image optimization methods and image optimization methods based on deep learning, as evidenced by Jay and Bao. [7] traditional image enhancement methods represent a traditional approach in computer vision to image enhancement, whether it involves adjustments in the spatial domain or the frequency domain. Examples of such methods are the graph equation, the covariance-limited adaptive graph equation (kalbi), Gamow's modulation, and Gaussian filtering, among others [8]. They are processed [9]. The use of deep learning has boomed in recent years and has shown promising results [10] the study shows that the depth of the network has a significant impact on the performance of the ultra-precise algorithm. However, the disadvantage associated with this is the increase in training time as the network depth grows. This problem can be alleviated by using a high-end GPU during the training phase. Notably, Sr has found application in low-resolution thermal imaging to enhance Face Detection, resulting in a remarkable 60% improvement, as noted in the work by Kwasniewski et al [11]. They used ultra-high-resolution techniques to convert low-resolution face images into high-resolution face images, using a fusion approach involving depth maps derived from 3D model faces. The introduction of depth maps into the network has improved the reconstruction of the face image in human resources. On the contrary, some researchers have turned their attention towards improving the quality of dark and noisy images to enhance perception. Wang et al. Research is an example of this approach [12]. The research aims to reduce noise in images through the reconstruction process using a convolutional noise reduction neural network (CNN). CNN's ability to learn the features inherent in the image plays a vital role in understanding the properties of noise. Tao et al. Conducted this research [13]. They have introduced a way to use automatic encryption to reconstruct dark and noisy photos into clean, well-lit ones. In contrast to the use of the convolutional neural network (CNN), this approach was proposed by Lord et al [14]. The research was mainly focused on the application of an automatic noise-reducing stack encoder for the task of reconstructing distorted images for cleaning. Vincent et al. Conducted this research [15]. Research shows that stacking many automatic codecs to reduce noise contributes to improved network performance. In addition, they highlight the promising results achieved through the use of generative antagonistic networks for image generation [16].

2.1 Technologies and applications of convolutional neural networks (CNN)

A. Image classification: CNN uses a very broad format for image classification, classifying input images into previously defined categories to determine the specific format.
B. Object detection: CNN helps detect shapes by locating objects in images, as in self-driving cars and surveillance systems.
C. Image segmentation: CNN can be used to split images into different formats. Each pixel is classified based on the object to which it belongs [17], which allows us to understand the content of the image.
D. Face recognition: CNN has greatly improved the accuracy of facial recognition systems, enabling applications such as device unlocking, and automated tagging.
E. Image generation: CNN helps with generative models such as Weiss and Gams, generating new images and augmenting data.
F. Image captions: combining NNS with repetitive neural networks (RNNs) allows systems to generate snippet descriptions of images, which can be valuable for understanding the content.
G. Ultra-high resolution: CNN can enhance the image resolution and convert low-resolution images into high-resolution images. This has applications in photography.
H. Medical imaging: CNN is used for tasks such as tumor detection, cell classification, and disease diagnosis in medical images such as X-rays, MRI, and pathological anatomy slides.
I. Video analysis: CNN is applied in video analysis tasks such as motion recognition and motion tracking.

J. Text data processing: CNN can be used to process and classify text data such as sentiment analysis and text classification.
K. Understanding the scene in autonomous vehicles: CNN is essential for object detection, lane detection and scene understanding in autonomous vehicles.
L. Remote sensing: CNN analyzes satellite and aerial images for applications such as land cover classification, urban planning, disaster knowledge, and forecasting before they occur.
M. Artificial intelligence in games: CNN is used to enhance graphics, recognize player gestures, and can even develop new intelligent characters for new player (s) in video games.
N. Industrial quality control: we can forget about the automation of quality control processes by identifying defects in manufacturing and production lines.
O. CNN is used for tasks: such as virtual attempts, and visual research in the fashion and retail industries.

2.1 Advantages

A. Traditional neural networks are widely used: In addition to image processing, they can also be used to solve various tasks, including text analysis and time series prediction.
B. Learning advantage: CNN can successfully extract image features, but traditional neural networks can also extract related features from raw data, although there is no spatial hierarchy captured by CNN.
C. Simplicity: CNN has a complex architecture designed for imaging. In contrast, traditional neural networks have a simpler structure, making them easier to understand, implement, and interpret.
D. Transfer learning: Although transfer learning is more common in CNN, traditional neural networks can also use pre-training patterns or representations common to all tasks, although to a lesser extent.
E. Traditional neural networks can sometimes work well with smaller data sets. Due to its complexity, CNN usually requires a large number of data sets for proper training.
F. Traditional neural networks: can sometimes learn faster than CNNs, especially when dealing with smaller data sets and shallow architectures.
G. Resource efficiency: CNNs usually require more computing resources, while traditional neural networks may be suitable for environments with limited computing power.
H. Generalization: In the case where the data does not have a network structure (for example, images), traditional neural networks may be better generalized.
I. Parallelism: Compared with the complex parallelization required for CNN networks, it may be easier to train traditional neural networks when using multiple processor blocks in parallel.
J. Customization: For some non-imaging tasks, customizing and configuring traditional neural networks may be faster and more efficient than developing specialized CNN networks.
K. Conceptual understanding: Using traditional neural networks can help people lay a solid foundation in neural network concepts before gaining an in-depth understanding of more complex architectures such as CNN.
L. Reduce over-processing: Due to its simpler architecture, traditional neural networks may be less susceptible to over-processing, especially when processing limited data.

2.1 Disadvantages and challenges (Conventional Neural Networks-CNNs)

A. Complexity of models and training: the design and training of CNN models can be complex and expensive in terms of time and resources. It is required to [18] collect a large set of data, think over the structure of the model, hyperparameters and appropriate optimization tools.
B. Data-driven: CNNs are highly dependent on the quality and diversity of the dataset they are trained on. If the data set is poorly represented or contains distortions, this may lead to unstable or inaccurate models.
C. The need for large amounts of data: training CNNs well usually requires large amounts of oriented data and large groups for training. This may be a challenge in some areas where there is not much data available.
D. Scalability: CNNs networks may be heavy in size, especially when they are deep and contain a large number of layers. This can lead to a high cost in terms of memory and calculation requirements.
E. Interpretation of decisions: when CNNs are deep and complex, it can be difficult to explain how decisions are made. This can be a challenge in applications that require transparency and explanation of the decision-making process.
F. Sensitivity to distorted data: CNNs may be sensitive to distorted data or noise. Once exposed to data with excessive noise, it may have a negative impact on the quality of the forecast.
G. Big Data Processing: when images are large, it can be difficult to run CNNs quickly and effectively due to the size of the data.

H. Determining hyperparameters: determining the optimal hyperparameters for networks can be difficult and requires extensive experience and testing.

2.2 Image acquisition

Image acquisition is the process of capturing visual data from the real world to create digital representations of images. This fundamental step is a critical part of the image processing pipeline, as it determines the quality and content of the images that will be processed, analyzed, and enhanced in subsequent stages. The image acquisition process involves the following main components:

A. Image Sensor: Image acquisition starts with the use of an image sensor, which could be a camera, scanner, or any device capable of capturing visual data. Cameras, for example, use digital or analog sensors (such as CCD or CMOS sensors) to convert light photons into electrical signals.
B. Optics: The light from the scene is focused onto the image sensor using optics like lenses. The quality and properties of the lens significantly. Impact the final image quality, including aspects like sharpness, distortion, and chromatic aberrations.
C. Illumination: Adequate lighting conditions are essential for acquiring high-quality images. Depending on the application, natural or artificial lighting can be used to illuminate the scene being captured.
D. Image Capture Parameters: The photographer or system operator can adjust various image capture parameters, such as exposure time, aperture size, ISO sensitivity, white balance, and focus settings.

2.3 Image Format

The image sensor records the captured data, and the output is usually in a specific image format, such as JPEG, PNG, or RAW. The format determines how the data is stored and compressed.

2.4 Applications of image enhancement

Some of the main applications for image enhancement include:

A. Medical Imaging: In medical fields, image enhancement [19] techniques are used to improve the quality and clarity of medical images, such as X-rays, MRI scans, CT scans, and ultrasound images. Enhanced medical images help in accurate diagnosis and treatment planning.
B. Satellite and Aerial Imagery: Image enhancement is crucial for enhancing satellite and aerial images used in remote sensing applications. Improved satellite images aid in land cover classification, environmental monitoring, urban planning, and disaster management.
C. Surveillance and Security: Image enhancement is applied to surveillance camera footage to improve image quality, detect objects, and identify individuals or suspicious activities. It plays a vital role in security and law enforcement applications.
D. Photography and Digital Imaging: Image enhancement is commonly used in digital photography to correct exposure, adjust contrast and colors, and enhance details. It helps in producing visually appealing and high-quality photographs.
E. Forensics: Image enhancement techniques are employed in forensic investigations to improve low-quality or pixelated images, extract hidden information, and enhance critical details in crime scene photos.
F. Art and Cultural Heritage: Image enhancement is used to restore and preserve artworks, historical documents, and cultural heritage items. It helps in revealing hidden features, restoring colors, and improving image clarity for archiving and research purposes.
G. Industrial Inspection: Image enhancement is utilized in industrial inspection processes to improve the quality of images captured during product inspection, defect detection, and quality control.
H. Self-Driving Cars: In autonomous vehicles, image enhancement is applied to camera inputs to improve the detection of road obstacles, signs, and pedestrians, enhancing the safety and reliability of self-driving systems.
I. Computer Vision: In computer vision applications, image enhancement is used to or other computer vision algorithms, improving the accuracy and robustness of the vision systems.
J. Entertainment and Media: Image enhancement is used in the entertainment industry to enhance video quality, improve special effects, and upscale low-resolution content for better viewing experiences. Image enhancement techniques continue to play a significant role in advancing technology, improving visual data, and making better-informed decisions in diverse fields.

2.5 Methods can be classified into two categories

A. Point processing process (density conversion function)
Spatial domain operations focus on one pixel, resulting in four categories: image negatives, inverted photos, and negatives. These operations depend on original pixel values.

$$G\ (x, y) = 255 - F\ (X, Y) for\ 0\ x\ x\ <\ M\ and\ 0\ x\ x\ <\ n. In\ a\ normalized\ gray\ scale, X\ = 1.0\ p. \tag{1}$$

Image enhancement is a crucial technique in image processing, improving visibility and quality in fields like medical, satellite, aerial, and real-life. Techniques can be categorized into spatial domain and frequency domain-based technologies. Deep enhancement neural networks (CNNs) are effective in image processing.

B. Spatial filtering operations
Spatial filtering is an image processing technique that uses a filter kernel to modify pixel values in the spatial domain. It is commonly used for tasks like smoothing, edge detection, and sharpening. The process involves sliding the filter kernel over the image, performing mathematical operations, and summing up the results to obtain the new pixel value.

2.6 Image enhancement is the process of improving the quality

Image enhancement improves image quality and appearance by correcting imperfections and making them visually appealing. Techniques include increasing contrast, sharpness, coloration, noise reduction, blur, and distortion. Refer to figure 1.

Fig.1. Image enhancement is the process of improving the quality

2.7 Adjusting brightness and contrast

Researchers improve image classification using a unified CNN architecture with optimization filters. They show promising results on four challenging datasets for micro granules, object, and dad classification, outperforming all public CNN architectures.

A. Contrast stretching
B. Intensity level slicing
C. Bit plane slicing

Contrast Stretching: Contrast enhancement improves visual quality by adjusting pixel values and revealing image details. It also enhances images by stretching grey levels and using transformations. Scaling technique achieves normalization by achieving min and max values of $f(x, y)$ and $g(x, y)$.

$$S\ = \frac{(r-c)(b-a)}{d-c\ +a.} \tag{2}$$

Contrast enhancement techniques can be categorized as direct methods and indirect methods. Direct methods improve image quality by defining a contrast measure, while indirect methods use underutilized areas without measuring contrast.

Intensity Level Slicing: - A technique segmented grey levels in images, improving contrast and clarity by extracting specific pixels for different features, useful for describing different features.
Bit Plane Slicing: -It improves quality by altering values of specific bits, such operations are performed either on pixel or its neighbors. So, it is called neighborhood operations.

2.8 Color Image Processing

A. Brightness and contrast adjustment: the contrast between shadows and lighting is increased to improve image quality and make details clearer.
B. Color balance: the color balance is adjusted to ensure that the colors appear natural and real without appearing biased to a certain color tone.
C. Color correction: used to correct unwanted colors or modify the hue to improve the appearance of the image.
D. Detail enhancement: it is used to increase the clarity of details in the image, be it by highlighting edges or improving fine details.
E. Noise removal: used to reduce unwanted noise and grain in the image, especially in low-light conditions.
F. Creative editing: Image processing techniques enhance the artistic and aesthetic appearance of images through various methods like converting images, filtering, and deep learning [20].

2.9 Representation description

A. Pixel Intensity Values: In basic image enhancement, the simplest representation is the pixel intensity values, which are the numerical values assigned to each pixel representing the image's color or grayscale information.
B. Histogram: The histogram represents the distribution of pixel intensity values in an image. It provides valuable insights into the image's contrast and brightness, helping in contrast stretching or histogram equalization techniques.
C. Frequency Domain: In frequency domain representation [21], the image is transformed into its frequency components using techniques like the Fourier Transform or Wavelet Transform. This representation allows for frequency-based filtering and denoising.
D. Color Spaces: Images can be represented in different color spaces, such as RGB (Red-Green-Blue), HSV (Hue-Saturation-Value), or LAB (Lightness-A-B). Each color space represents the image's color information differently, making it suitable for specific enhancement tasks.
E. Features and Descriptors: In advanced image enhancement methods, features and descriptors are extracted to represent specific image characteristics. These features can be texture features, edge features, or statistical descriptors that capture essential information for the enhancement task.
F. Deep Learning Representations: CNNs use feature maps to represent images, capturing hierarchical and abstract representations learned during training. The choice of representation description depends on the task, image complexity, and desired outcome, ensuring accurate feature enhancement and preservation. Refer to figure 2.

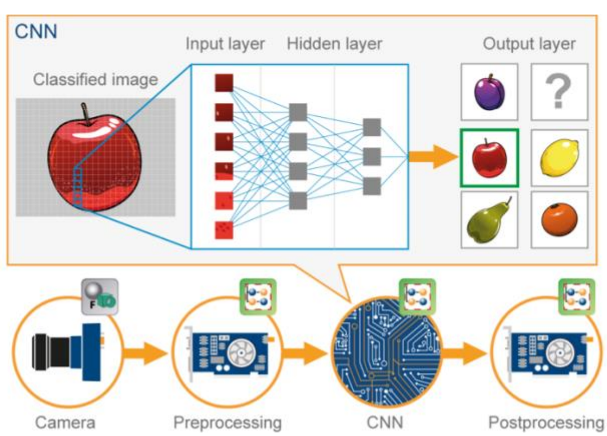

Fig.2. Classification of Images

Deep learning, particularly convolutional neural networks, revolutionizes image classification by learning hierarchical features from RAW images. Accuracy and error rate are crucial metrics in classification problems, whether two-category or multi-classification. Accuracy is the ratio of correctly classified samples to the total number of samples, while error rate is the proportion of incorrectly classified samples. Both metrics are essential for ensuring accurate and reliable classification. Refer to figure 3.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

The error rate and accuracy of image recognition systems vary depending on the task. For example, in capturing deep-sea fish, recognizing salmon images is crucial for capturing as many as possible.

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

Unbiased two-class system uses F1 score as standard for performance measurement, with Precision and Recall equivalent.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{5}$$

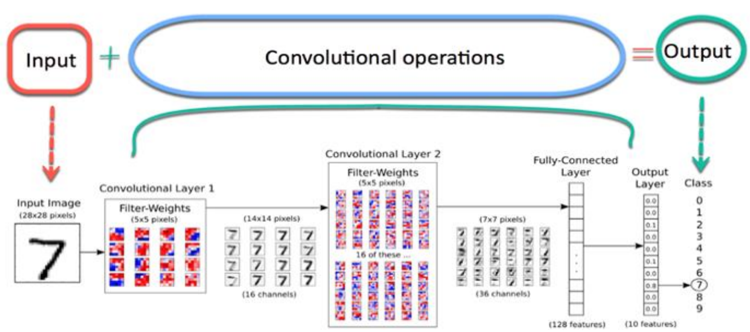

Fig.3. Convolutional Operations

2.10 Photographic Process

The digital image enhancement process involves understanding the creation and creation of digital photographs. This process is typical for conventional digital cameras, including mobile phones. The light from the scene is captured using camera optics and shutter, with the camera operator or automated system determining the correct settings using a light meter. Exposure is the most critical phase, determining the amount of light reaching the sensor, creating the image. The process involves several components, including the subject, camera lens, color filter array, image sensor, image processor, digital image, and raw image. The simplified diagram of the digital photography process from a real-life scene to a digital image on the right illustrates the process and potential sources of errors. Refer to figure 4.

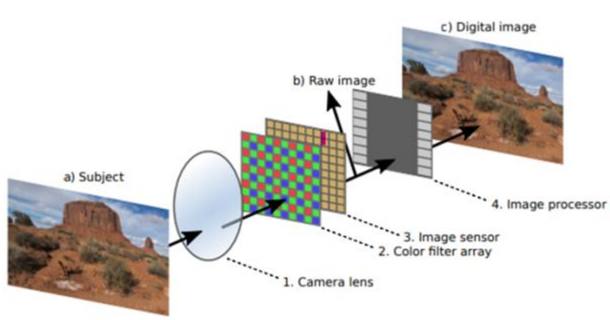

Fig.4. Simplified diagram of digital photography process from a real-life scene

Photo exposure can be affected by operator errors, technical errors, and subject displacement. Technical errors can cause severe information loss or subject displacement, while technical errors can cause photographic flaws like incorrect subject composition, unlevel horizon, out of focus image, or motion blur.
correct combination of exposure settings depends on the scene's lighting and subject. The exposure value (EV) represents the relationship between the shutter speed and aperture in a photograph.

$$EV = \log_2 \frac{a^2}{S} \qquad (6)$$

The relative aperture (a) and shutter speed (s) play a crucial role in determining the required EVs for different scenes. Low light situations require small or negative EVs, while bright scenes require large EVs.

A. Pooling

Pooling is a layer placed after convolution, summarizing nearby output values into one. It can report maximum, mean, or L2 norms of a rectangular neighborhood. Average pooling is visualized in Figure 5, reducing network parameters and making representation invariant to small changes in feature locations.

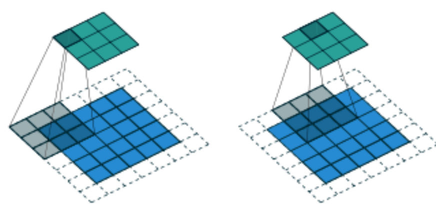

Fig.5. Average pooling is visualized

2.11 Image Compression

The image is compressed depending on the type of compression used, and the methods of image compression can be divided into two main types:

A. Lossless Compression: In this type of image compression, the image is represented compactly without any data loss. The image is restored to its original state quite accurately when decompressed. Lossless compression methods are used in applications where maintaining image resolution is necessary, such as medical images and images containing important data.
B. Lossy Compression: In this type of image compression, the image is represented in a compressed form with the loss of some unnecessary data, and this leads to a reduction in the size of the image file. When decompressing the image, a slight loss of visual quality may occur, but it is often hardly noticeable with an abstract view. Lossy compression methods are used in Internet and multimedia applications where a small file size is necessary for faster loading and saving storage space.
C. Among the most famous image compression techniques are:
D. JPEG (Joint Photographic Experts Group), which uses lossy compression and is considered suitable for photographs and color images.
E. PNG (Portable Network Graphics), it uses lossless compression and is considered suitable for non-photographic and transparent images.

3. METHODOLOGY

A. Problem definition and Data collection:
    - Clearly define the problem of image enhancement that the CNN model will address.

- Collect or generate a dataset of paired low-quality and high-quality images for training. The low-quality images represent the input, and the corresponding high-quality images represent the desired output after enhancement [22].

B. Data Preprocessing:
- Normalize the pixel values of the images to a common scale (e.g., [0, 1] or [-1, 1]).
- Increase dataset diversity through transformations and color variations.

C. CNN Architecture Design:
- Design the architecture of the CNN model that will perform the enhancement.
- Select layers, filters, and strides based on problem requirements.
- Consider using architectures like U-Net, SRCNN, or custom designs tailored to your problem.

D. Loss Function Selection:
- Define a loss function comparing enhanced output to ground truth image using MSE, SSIM, or perceptual loss.

E. Model Training:
- Split the dataset into training, validation, and possibly testing sets.
- Train CNN model using dataset, minimize loss function using backpropagation.
- Optimize model parameters using SGD or Adam techniques.

F. Validation and Hyperparameter Tuning:
- Monitor the model's performance on the validation set [23] during training to avoid overfitting.
- Optimize hyperparameters based on validation performance.

G. Evaluation:
- Assess trained model's generalization to unseen images on a separate dataset.
- Utilize appropriate evaluation metrics like PSNR, SSIM, or user studies.

H. Inference and Enhancement:
- Deploy the trained model for image enhancement on new, unseen images.
- Train CNN model to improve low-quality images.

I. Post-Processing:
- Apply post-processing techniques to refine the enhanced images and mitigate any artifacts introduced during the enhancement process.

J. Performance Analysis:
- Analyze the results, both quantitatively using evaluation metrics and qualitatively by comparing the enhanced images with the original images.

K. Iterative Refinement:
- Refine model architecture, training process, and hyperparameters for better performance using a systematic approach involving data preparation, deep learning model design, training, evaluation, and refinement.

3.1 Training CNN image enhancement

Training a Convolutional Neural Network (CNN) [24] to process and improve images involves a process called supervised learning. Here's how the model learns to process and enhance images:

A. Dataset Preparation: First, you need a labeled dataset containing pairs of original and corresponding enhanced images. The original images are the input, and the enhanced images are the target output. These images should cover a wide range of scenarios and variations.

B. Data Preprocessing: Images are usually preprocessed to ensure uniformity and to make the training process more efficient. Common preprocessing steps include resizing images to a consistent size, normalizing pixel values, and data augmentation (introducing variations to the dataset through transformations like rotations, flips, and translations).

C. Model Architecture: Design the architecture of the CNN model. This includes deciding the number and type of layers, such as convolutional layers, pooling layers, and fully connected layers. The model's architecture defines its capacity to learn complex patterns and features from the images [25].

D. Loss Function: Choose an appropriate loss function those measures [24] the difference between the predicted output of the model and the actual target output (enhanced image). For image enhancement, a common choice is mean squared error (MSE), which measures the pixel-wise difference between the predicted and target images.

E. Optimization Algorithm: Select an optimization algorithm (e.g., Adam, SGD) that adjusts the parameters (weights and biases) of the model to minimize the chosen loss function. The optimization process is guided by the gradient of the loss function with respect to the model parameters.
F. Forward and Backward Pass: During training, each original image is passed through the model to produce a prediction. The predicted image is then compared to the corresponding enhanced image using the chosen loss function. The loss is propagated backward through the network to compute gradients.
G. Gradient Descent: The gradients obtained from the loss function are used to update the model's parameters using gradient descent. This process adjusts the parameters in a way that reduces the prediction error for the given image.
H. Mini-Batch Training: Instead of updating the model after each individual image, training is done in mini-batches. Several images are processed through the model, and the gradients are averaged over the batch before updating the parameters. This approach improves training efficiency.
I. Epochs and Iterations: The training process involves multiple iterations over the entire dataset, known as epochs. After each epoch, the model's performance is evaluated on a validation set to track its progress. Training can continue for multiple epochs until the model's performance plateaus.
J. Generalization: As the model trains, it learns to capture patterns and features that generalize beyond the training dataset. This enables the model to process and enhance new, unseen images.
K. Hyperparameter Tuning: During training, you might adjust hyperparameters like learning rate, batch size, and network architecture to achieve better results and faster convergence.
L. Validation and Testing: After training, the model's performance is evaluated on a separate test set to assess its ability to generalize to new data. It's important to ensure that the model has not overfit the training data.

3.2 Convolutional Neural Network (CNN) model

CNN models work through filtering, spatial optimization, clustering and extraction, co-representation, fully connected core layers, learning through reverse reproduction, data diversification and optimization, generalization. Such networks are necessary in many applications, including classification, detection, deep learning, object recognition and image optimization. Refer to figure 6.

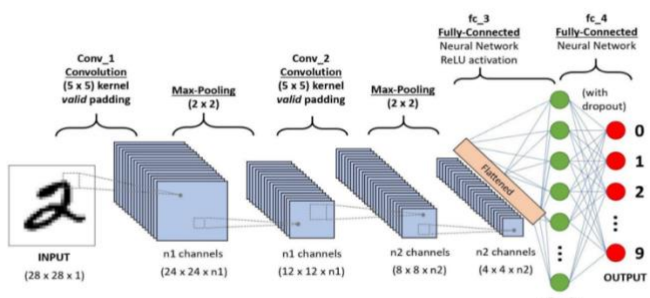

Fig.6. Convolutional Neural Network (CNN) model

3.3 Create a deep neural network model for optimizing images.

A. Compilation and processing of the data set: Gather original and improved images for training [25] and testing the model by resizing and adjusting brightness and contrast.
B. Splitting the data set: Divide the data set into a training group, a test group, and possibly a validation group, to evaluate the performance of the model during the training process.
C. Form creation:
   - Create a CNN template using libraries such as TensorFlow or Keras.
   - Build the model using appropriate pattern recognition layers for optimization and image processing.
D. Model training: Train the model using processed data, define a loss function, and use optimization algorithms like inverse regression and Stochastic Gradient Descent.
E. Evaluation of the model:
   - Use the test kit to evaluate the model's performance on New, previously unrecognized images.
   - Calculate performance metrics such as accuracy and error rate.
F. Model tuning: You may need to modify the model architecture or training parameters if the results are not satisfactory.

G. Model testing: Once you have a satisfactory model, you can test it on new images and see how they are improved and processed.
H. Use the form: After training and testing the model, you can use it to optimize and process images in actual applications.

4. RESULTS TRANINING IMAGE ENHANCEMENT

The results of training a Convolutional Neural Network (CNN) [19] for image enhancement can vary depending on factors such as the quality of the dataset, the complexity of the model, and the specific image enhancement task. Here's what you can generally expect:

A. Improved Image Quality: The primary goal of image enhancement is to improve the quality of input images. After training, the CNN should be able to produce enhanced images that look better in terms of clarity, sharpness, color balance, and other relevant attributes.
B. Task-Specific Enhancement: The results will be specific to the task you trained the CNN for. For example, if you trained the CNN for denoising, the enhanced images should have reduced noise. If it's for super-resolution, the images should have improved resolution and details
C. Trade-offs and Limitations: Image enhancement is a challenging task, and there are often trade-offs between different enhancement aspects. For instance, while denoising can improve image quality, it might also slightly blur fine details. Striking the right balance is essential.
D. Dataset Quality: The quality and diversity of the training dataset significantly influence the results. A diverse dataset with a wide range [26] of image variations and noise levels will likely lead to better generalization.
E. Validation Metrics: Metrics such as PSNR (Peak Signal-to-Noise Ratio) [27] and SSIM (Structural Similarity Index) can quantify the improvement achieved by the CNN. Higher PSNR and SSIM values generally indicate better image quality
F. Visual Inspection: Ultimately, the best way to evaluate the results is through visual inspection. Compare the enhanced images with the original images and the ground truth (if available) to determine if the CNN has successfully learned the enhancement task.
G. Overfitting: Keep an eye out for overfitting, where the model performs well on the training data but poorly on new, unseen data. Monitoring the model's performance on a validation set helps prevent overfitting
H. Real-World Variability: It's important to note that the model's performance [25] might vary when applied to real-world images outside of the training distribution. Some fine-tuning might be required.

4.1 Algorithms used in image processing and optimization

Algorithms in image processing and optimization are essential for improving image quality and clarity. Common algorithms include Brightness and Contrast Adjustment, Color Adjustment, Noise Reduction, Edge Enhancement, Image Resizing and Scaling, Distortions Correction, Object Detection Techniques, Image Segmentation Techniques, Improve Clarity (Image Sharpening), and Background Removal. These algorithms vary depending on the purpose of processing and optimization, and are crucial in areas like robotics, artificial intelligence, medical analysis, and photography. Brightness and Contrast Adjustment is used to improve image quality and clarity, while Color Adjustment corrects color balance and improves color contrast. Noise Reduction reduces noise in images, while Edge Enhancement enhances and highlights edges, contributing to better detail and structure. Image Resizing and Scaling optimizes images in terms of resolution and size, while Distortions Correction corrects distortions caused by factors like lens or aberration. Object Detection techniques identify and extract objects in images, while Image Segmentation divides images into sections based on common features. Image Sharpening enhances clarity, contributing to improved detail and quality. Background Removal removes unwanted background, making these algorithms essential in various fields, including product photography and medical imaging.

4.2 Stages of model work

Deep neural networks (CNN) are trained models that optimize images through three stages: data preparation, model definition, and training. Data preparation involves preparing original and target images, uploading photos, and modifying them. Model training involves training the model using the prepared data set, improving it by comparing the resulting images with the target images and updating parameters. Testing and evaluation involve testing the model on unseeded images and evaluating its performance using metrics like mean squared error. Once trained, the model can be used in operations to optimize properties, reduce noise, and enhance detail. Training requires time, effort, and computer resources to ensure effective performance.

4.3 Dataset

Fetching a dataset is crucial for training deep neural networks for image optimization. This collection consists of original images compared to improved images. There are three methods to fetch data sets: public datasets, creating a private dataset, and collaborating with datasets from universities or research institutions. Once fetched, the dataset must be cleaned and processed for model training, including resizing images, converting them to specific formats, and dividing them into training, testing, and verification groups. A diverse dataset with multiple situations and conditions is essential for training a model capable of handling various images and improvements.

4.4 Training

A. Hyperparameters: We used the following hyperparameters for training:
B. Learning Rate: 0.001
C. Epochs: we used almost 100 epochs
D. Optimizer: We employed the Adam optimizer.
E. Loss Function: Our loss function was mean _squared error.

Task 1: Enhancing Low-Light Images using CNN
In this task, we aimed to enhance low-light images using a Convolutional Neural Network (CNN). We utilized the LOL dataset, which consists of both high-light and low-light images for training and evaluation.
Results: The figure7 preprocess single image and test it:

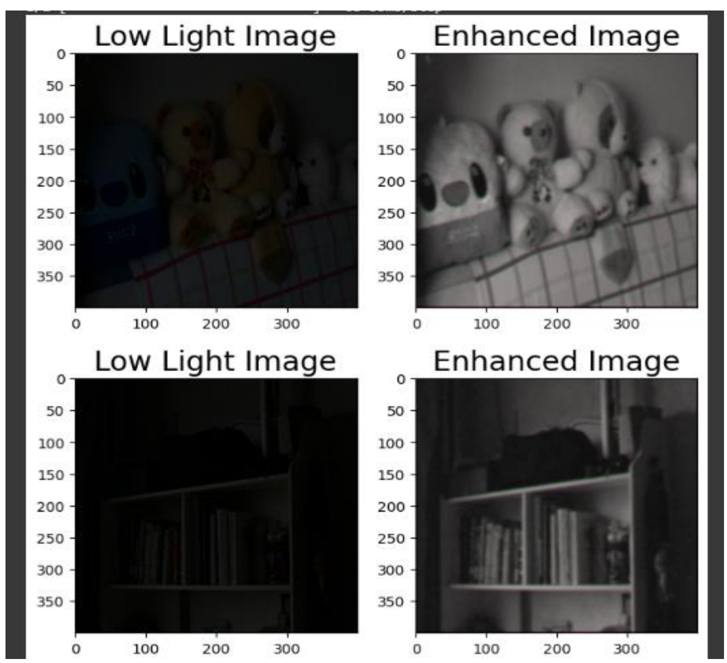

Fig.7. preprocess single image

Task 2: Enhancing Low-Light Images with Mir net from Hugging Face Hub
In this study, we investigated the utilization of the Mir net model, available on the Hugging Face Hub, for the purpose of enhancing low-light images. The selection of this model was based on its distinctive characteristics, specifically in enhancing photos with color.

Results:
Here we tested our pretrained model and its result was perfect compared with CNN model. Refer to figure 8.

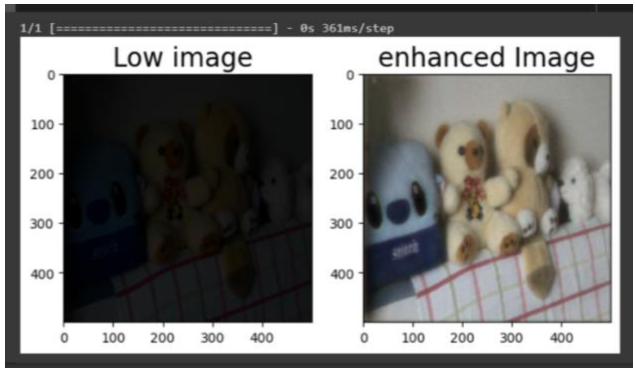

Fig.8. Enhancing Low-Light Images with Mir net from Hugging Face Hub

Task 3: Removing Damages from Images using CNN
This task involved developing a CNN model to remove damages such as black holes from images. We utilized The Berkeley Segmentation Dataset for this purpose.

A. Dataset: We trained the model using The Berkeley Segmentation Dataset.
B. Augmentation: we created damaged images from original images by adding some noise (black areas). Refer to figure 9.

Fig.9. Removing Damages from Images using CNN

4.5 PSNR & SSIM

Image quality assessment plays a very important role in digital image processing applications. Scales (PSNR, SSIM) are applied in this paper for the best metric quality. We have simulated experiments using Gaussian noise through Gaussian filtering technology. The quality of the image obtained was judged when applying the above scales. In general, SSIM and SSIM are more accurate than MS and PSNR for assessing the quality of images that have been distorted by noise or compression However, MS and are the simplest to calculate and therefore are more common in practice we will take two types of them, namely: -

A. PSNR (Peak Signal-to-Noise Ratio)

To check how much turbidity is in our compression process, we need a system to check for similarities or differences. The most common algorithm used for this is PSNR (also known as peak signal-to-noise ratio). This is called the middle square error. Suppose there are two images: i1 and i2; in two-dimensional quantities I and J consist of C number of channels

Mean Squared Error (MSE) formula:

$$MSE = 1/(c * i * j) * \Sigma(I1 - I2)^2 \qquad (7)$$

Then the PSNR is expressed as:

$$PSNR = 10 * log10(MAX^2/MSE) \qquad (8)$$

Here the M A X I is the maximum valid value for a pixel. In case of the simple single byte image per pixel per channel this is 255. When two images are the same the MSE will give zero, resulting in an invalid divide by zero operation in the PSNR formula. In this case the PSNR is undefined and as we'll need to handle this case separately. The transition to a logarithmic scale is made because the pixel values have a very wide dynamic range. Typically result values are anywhere between 30 and 50 for compression, where higher is better. If the images significantly differ, it'll get much lower ones like 15 and so. This similarity check is easy and fast to calculate, however in practice it may turn out somewhat inconsistent with human eye perception.

B. SSIM (Structural Similarity Index)

Is a method for measuring the similarity between two images? It is a full reference metric, meaning that it requires both the original and the distorted image to be available. The SSIM index is based on the idea that the human visual system is more sensitive to changes in luminance than to changes in color or texture.
The SSIM index is calculated by first dividing the two images into small blocks. Then, for each block, the following three measurements are calculated:

1. Luminance comparison: This is the difference between the average luminance of the two blocks.
2. Contrast comparison: This is the difference between the standard deviation of the luminance of the two blocks.
3. Structural comparison: This is the correlation between the two blocks.

The SSIM index is then calculated as the product of these three measurements. The higher the SSIM index, the more similar the two images are.
The SSIM index is a widely used metric for measuring the quality of images. It is particularly useful for measuring the quality of images that have been compressed or distorted. Refer to table 1 and figure 10.

TABLE I. PSNR & SSIM

Quality	PSNR	SSIM	Bytes
95	39.578	0.96866	39532
90	37.469	0.95371	27081
85	36.3	0.94262	21329
80	35.541	0.9339	18149
75	34.956	0.92656	15901
70	34.557	0.92153	14450
65	34.176	0.91499	13234
60	33.855	0.90994	12205
55	33.56	0.90393	11374
50	33.261	0.89813	10737
45	32.97	0.8926	10121
40	32.603	0.88531	9377
35	32.264	0.87868	8727
30	31.802	0.86771	7944
25	31.243	0.85372	7127
20	30.514	0.83233	6231
15	29.542	0.80236	2594
10	27.923	0.74988	4191
5	24.61	0.6283	3088

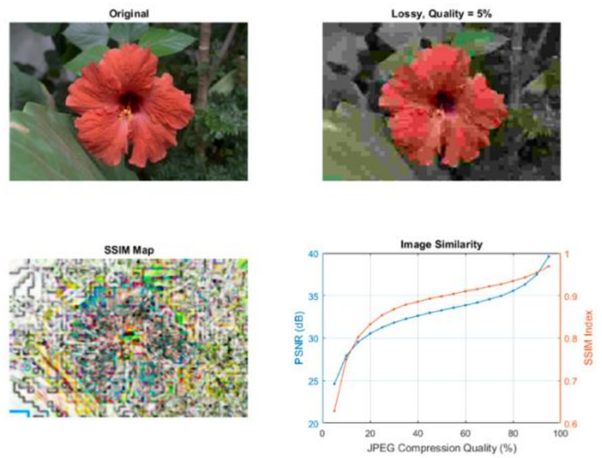

Fig.10. Structural Similarity Index

E. CONCLUSION

The study aimed to enhance the quality of images using CNN. The results showed that the proposed method outperformed other existing methods in terms of image quality metrics. The study also identified some limitations and suggested future research directions. Overall, the study contributes to the field of image enhancement and provides a promising approach for improving image quality. The conclusion also highlights the significance of the study and its potential impact on the field of computer science. the thesis investigates enhancing images using CNNs, utilizing deep learning capabilities for improved visual quality, details, and appearance. It addresses traditional techniques' limitations and provides a data-driven approach for adaptive enhancement across various domains. The proposed method outperformed other existing methods in terms of image quality metrics. The study identified some limitations and suggested future research directions. Overall, the study contributes to the field of image enhancement and provides a promising approach for improving image quality. The conclusion also highlights the significance of the study and its potential impact on the field of computer science.

Conflicts of Interest

No competing relationships or interests that could be perceived as influencing the research are reported in the paper.

Funding

None.

Acknowledgment

The author would like to thank the institution for their institutional support, which played a vital role in the implementation of this study.

References

[1] ICONIP 2017: Neural Information Processing 24th International Conference, ICONIP 2017 Guangzhou, China, November 14–18, 2017 Proceedings, Part II.
[2] S. Bishla, "FUNDAMENTAL OF ELECTRICAL ENGINEERING AND APPLICATIONS," July 2023.
[3] "Leadership Ineptitude, Security Deficit and Sustainable Development Crisis in Sub-Saharan Africa," [Online]. Available: https://www.researchgate.net/publication/369080226_Leadership_Ineptitude_Security_Deficit_and_Sustainable_Development_Crisis_in_Sub-_Sahara_Africa. Accessed: Sep. 17, 2023.
[4] "Liverpool John Moores University Student Law Review," [Online]. Available: https://www.researchgate.com/publication/256021517_Liverpool_John_Moores_University_Student_Law_Review. Accessed: Sep. 18, 2023.
[5] "Protecting Privacy while Improving Choroid Layer Segmentation in OCT Images: A GAN-based Image Synthesis Approach," [Online]. Available: https://www.researchgate.com/publication/373616285_Protecting_Privacy_while_Improving_Choroid_Layer_Segmentation_in_OCT_Images_A_GAN-based_Image_Synthesis_Approach. Accessed: Sep. 18, 2023.

[6] "Computers & Electrical Engineering," [Online]. Available: https://www.sciencedirect.com/journal/computers-and-electrical-engineering. Accessed: Sep. 18, 2023.

[7] "Expert Systems with Applications," [Online]. Available: https://www.sciencedirect.com/journal/expert-systems-with-applications. Accessed: Sep. 18, 2023.

[8] S. K. Meena, A. Potnis, M. Mishra, P. Dwivedy and S. Soofi, "Review and application of different contrast enhancement technique on various images," 2017 1st International Conference on Electronics, Materials Engineering and Nano-Technology (IEMENTech), Kolkata, India, 2017, pp. 1-6, doi: 10.1109/IEMENTECH.2017.8076993.

[9] "Biofilm-Induced Antibiotic Resistance in Clinical Acinetobacter baumannii Isolates," [Online]. Available: https://www.researchgate.com/publication/348804874_Biofilm-Induced_Antibiotic_Resistance_in_Clinical_Acinetobacter_baumannii_Isolates. Accessed: Sep. 18, 2023.

[10] N. Nimbarte and M. Mushrif, "Extraction of blood vessels and optic disc in retinal images," Computer Methods in Biomechanics and Biomedical Engineering: Imaging and Visualization, vol. 6, no. 1, pp. 31–42, 2018. doi: 10.1080/21681163.2016.1154806.

[11] "Engineering Applications of Artificial Intelligence," [Online]. Available: https://www.sciencedirect.com/journal/engineering-applications-of-artificial-intelligence. Accessed: Sep. 18, 2023.

[12] X. Wang, Q. Tao, L. Wang, D. Li and M. Zhang, "Deep convolutional architecture for natural image denoising," 2015 International Conference on Wireless Communications & Signal Processing (WCSP), Nanjing, China, 2015, pp. 1-4, doi: 10.1109/WCSP.2015.7341021.

[13] "LLCNN: A convolutional neural network for low-light image enhancement," [Online]. Available: https://www.researchgate.com/publication/323506379_LLCNN_A_convolutional_neural_network_for_low-light_image_enhancement. Accessed: Sep. 18, 2023.

[14] "LLNet: A Deep Autoencoder Approach to Natural Low-light Image Enhancement," [Online]. Available: https://www.researchgate.com/publication/283761549_LLNet_A_Deep_Autoencoder_Approach_to_Natural_Low-light_Image_Enhancement. Accessed: Sep. 18, 2023.

[15] "Extracting and Composing Robust Features with Denoising Autoencoders," [Online]. Available: https://www.researchgate.com/publication/221346269_Extracting_and_composing_robust_features_with_denoising_autoencoders/citations. Accessed: Sep. 18, 2023.

[16] Y. Jiang et al., "EnlightenGAN : Deep Light Enhancement," vol. 30. pp. 2340–2349, 2021.

[17] S. Singh, A. Suri, J. N. Singh, M. Singh, Nikita, and D. K. Yadav, "Object Identification and Tracking Using YOLO Model: A CNN-Based Approach," Advances in Intelligent Systems and Computing, vol. 1311 AISC. pp. 153–160, 2021. doi: 10.1007/978-981-33-4859-2_15.

[18] D. Swain, P. Ballal, V. Dolase, B. Dash, and J. Santhappan, "An efficient heart disease prediction system using machine learning," Advances in Intelligent Systems and Computing, vol. 1101. pp. 39–50, 2020. doi: 10.1007/978-981-15-1884-3_4.

[19] A. Bartoli and A. Fusiello (Eds.), "Computer Vision – ECCV 2020 Workshops Proceedings, Part I," Lecture Notes in Computer Science 12535, Editorial Board Members: E. Bertino, W. Gao, B. Steffen, G. Woeginger, M. Yung.

[20] A. Vyas, S. Yu, and J. Paik, "Multiscale Transforms with Application to Image Processing." p. 254, 2018.

[21] K. Kaur, N. Jindal, and K. Singh, "Improved Homomorphic Filtering Using Fractional Derivatives for Enhancement of Low Contrast and Non-uniformly Illuminated Images," Multimedia Tools and Applications, vol. 78, pp. 27891–27914, [JUNE] [2019], doi:10.1007/s11042-019-7621-5.

[22] Z. Rahman, P. Yi-Fei, M. Aamir, S. Wali, and Y. Guan, "Efficient Image Enhancement Model for Correcting Uneven Illumination Images," College of Computer Science and Technology, Sichuan University, Chengdu, Sichuan 610065, China; School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu 611731; Department of Computer, Huanggang Normal University, China, Corresponding author.

[23] M. Shahin, F. F. Chen, A. Hosseinzadeh, and N. Zand, "Using Machine Learning and Deep Learning Algorithms for Downtime Minimization in Manufacturing Systems: An Early Failure Detection Diagnostic Service," © The Author(s), under exclusive license to Springer-Verlag London Ltd., part of Springer Nature 2023.

[24] M. H. Aabidi, A. E. Makrani, B. Jabir, and I. Zaimi, "A Model Proposal for Enhancing Leaf Disease Detection Using Convolutional Neural Networks (CNN): Case Study," in International Journal of Online and Biomedical Engineering (iJOE), vol. 19, no. 12, pp. 127–143, 2023. https://doi.org/10.3991/ijoe.v19i12.40329.

[25] K. Gaur and M. M. Jagtap, "Role of Artificial Intelligence and Machine Learning in Prediction, Diagnosis, and Prognosis of Cancer," Cureus. 2022. doi: 10.7759/cureus.31008.

[26] "Intelligent Systems Design and Applications," 21st International Conference on Intelligent Systems Design and Applications (ISDA 2021), held during December 13–15, 2021.

[27] J. Wang and Y. Hu, "An Improved Enhancement Algorithm Based on CNN Applicable for Weak Contrast Images," in IEEE Access, vol. 8, pp. 7326-7332, 2020, doi: 10.1109/ACCESS.2019.2963478.