



Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)



A Hybrid Deep Learning and Color Space Model for Digital Image Enhancement

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ARTICLE INFO

Article history:

Received: 16 /02/2026

Revised form: 02 /04/2026

Accepted : 06 /04/2026

Available online: 30 /06/2026

Keywords:

Digital Image Enhancement,

Deep Learning,

Contrast Enhancement

Color Enhancement

ABSTRACT

Image contrast enhancement is crucial in digital image processing. Enhancing contrast highlights image details, improves lighting, and focuses on key features that help maintain image quality and enhance visual perception in various fields such as computer vision, medical imaging, and surveillance systems. Deep learning models are applied to improve the contrast and brightness of digital images while preserving fine details and minimizing distortion. This article presents a method for improving image appearance using a hybrid application of deep learning and digital image processing techniques with different color systems to obtain an enhanced image from the original. Three color models and four deep learning techniques are used with contour transformations to capture the finest details of the digital image, in addition to applying contrast enhancement techniques to increase image clarity. The color system of a color image is converted from RGB to other color systems. The color system is then divided into its original layers, which are further deconstructed using contour transformations. Contrast enhancement techniques are then applied to increase the contrast in the digital image, thus training the model to optimize image colors. A range of metrics were also used to measure the generalizability of the proposed system (PSNR, SSIM, accuracy). The results showed that the best color system was HSV, when combined with the ResNet50 deep learning model. The results were as follows: PSNR = 44.2, SSIM = 0.9952.

<https://doi.org/10.29304/jqcm.2026.18.22658>

1. Introduction

A Digital image is a visual representation for an object or scene that can be saved and processed in a digital device where each image is a 2-dimensional array that consisted of pixels which is the smallest element in the image that have a location and value [1]. Digital image is distinguished from traditional images, where digital images can be improved and edited using different image processing techniques like denoising, deblurring, contrast enhancement, brightness enhancement and feature extraction. Nowadays digital images are crucial in diverse domains including: computer science, medical imaging, communications, security and surveillance systems [2].

The image quality could be diminished due to noise, low contrast, blurring, the use of low quality imaging tools or during transmission. This degradation alters the shape or size of the object inside the image leading to generate a distorted image. Image enhancement is the solution to overcome the degradation problem in digital images which aims to produce suitable images for rendering or for further image analysis [1][2]. Image enhancement techniques

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Communicated by 'sub editor'

encompass denoising, color enhancement, contrast enhancement, and brightness enhancement. These techniques are utilized to remove noise, sharpen edges, enhance illumination to retrieve the key features. They are broadly adopted in various fields such as medical imaging, remote sensing, surveillance, forensic analysis, and consumer photography, where the clarity and perceptibility of visual information are critical factors that influence image data analysis directly [3].

Image enhancement techniques are categorized into two main categories: spatial domain and frequency domain. Spatial domain approaches process the raw pixels values in the image matrix within a specific area. These methods apply functions to modify the values of individual pixels while frequency domain methods process on the Fourier transform of the image [4].

Deep learning is a subfield of machine learning, that include multi layers that perform mathematical operations to process the input data and extract intricate features to learn complex patterns and reduce the need for human intervention. Deep learning evolution helped in addressing diverse image processing challenges. Deep learning techniques such as convolutional neural networks enabled restoring fine details and produced a high quality results [5]. Deep learning methods can handle large datasets which leads to widely deployment of these techniques in different tasks such as image processing, speech recognition, medical diagnosis, autonomous driving. Deep learning models' ability to function hierarchically and automatically extract features through nonlinear transformation layers improved the performance and allowed the system to adapt to different imaging issues and plays a crucial role in image enhancement[6][7].

2. Related Work:

This paragraph presented a set of articles that depended on deep learning techniques in enhancing digital image quality:

Chen et al [8] utilized different deep learning methods (U-Net, Autoencoder CNN, GAN) to improve MRI images by enhancing quality, mitigating noise and preserving fine details. MRI Images from a clinical dataset were used. PSNR and SSIM were applied to measure the performance, the obtained results was (30-40, 0.9) respectively. It is prone to overfitting and generalization issues and high computational demand of DL models.

Zhu et al [9] developed an edge enhancement network for low-light images while preserving edge/ detail data, noise reduction, and contrast correction by using a CNN-based fusion network that generates multiple synthetic exposures. It shown by experiment the dependence on quality of generated synthetic exposures and the need to large paired training data. The datasets that has been utilized are from LOL dataset which contains a paired low light and normal light colored images for natural scenes, the outcome shows that the PSNR was between(21 to 24), and SSIM ranges from 0.85 to 0.88.

May et al [10] propose a self-calibrated illumination (SCI) framework for fast, robust, and flexible low-light image enhancement using a YUV color space for smoothing loss. This method is dependent on the input data quality and unsupervised loss may not cover all real cases. The results shows that PSNR is 20.44 and SSIM is 0.893 when applying the enhancement on a low light images.

Zhao et al [11] developed a Deep Learning framework (U-Net based architecture with high-resolution representation and multiple frame inputs) to improve OCT (Optical Coherence Tomography) image quality and compare with image averaging. OCT images suffer from speckle noise and require multiple scans for averaging and motion artifacts. 815 OCT sets (359 normal, 456 diseased eyes) of images utilized resulting in PSNR = 40.1 and SSIM = 0.97.

Hwang et al [12] adopted a two-stage deep learning model (Pix2Pix GAN + ResNet; compared with Pix2Pix + VGG16 / InceptionV3) to predict optimal imaging parameters during vitreoretinal surgery for improved visibility using deep learning and to improve image brightness and contrast. However, it is limited to retrospective and in-vitro experiments; also it is not fully real-time. 212 optimized surgical stills and 121 high-res ERM fundus images were used and best results obtained were: PSNR = 34.59 ± 5.34 and SSIM = 0.88 ± 0.08 .

3. Color Space

Color space or color models are mathematical methods to represent colors in digital images where the main purpose of the color system is to standardize the representation of the colors through different applications depending on the requirements of each distinct task [13] [14]. Color models can be converted from one to another by performing specific formula. This conversion is important due to different color models are utilized for different applications and purposes [15][16].

4. Color Models Transformations

RGB color space can be converted to other color space by applying a specific formula for each conversion. [17][18]

RGB to HSI [19]:

$$I = \frac{R+G+B}{3} \dots\dots\dots(1)$$

$$H = \cos^{-1} \left[\frac{R + \frac{1}{2}G - \frac{1}{2}B}{\sqrt{R^2 + G^2 + B^2 - RG - RB - GB}} \right], \text{ if } G > B \text{ or } \dots\dots\dots(2)$$

$$H = 360^\circ - \cos^{-1} \left[\frac{R + \frac{1}{2}G - \frac{1}{2}B}{\sqrt{R^2 + G^2 + B^2 - RG - RB - GB}} \right], \text{ if } B > G \dots\dots\dots(3)$$

$$S = 1 - \frac{M^3}{R+G+B} [\min(R, G, B)] \dots\dots\dots(4)$$

RGB to HSV

RGB color space can be transform to HSV color system through a specific mathematical formula[20], that are listed as following :

Hue calculation:

$$H = \begin{cases} 0^\circ & \Delta = 0 \\ 60^\circ \times \left(\frac{G'-B'}{\Delta} \text{ mod } 6 \right), C_{max} = R' \\ 60^\circ \times \left(\frac{B'-R'}{\Delta} + 2 \right), C_{max} = G' \\ 60^\circ \times \left(\frac{R'-G'}{\Delta} + 4 \right), C_{max} = B' \end{cases} \dots\dots\dots(5)$$

Saturation calculation:

$$S = \begin{cases} 0, C_{max} = 0 \\ \frac{\Delta}{C_{max}}, C_{max} \neq 0 \end{cases} \dots\dots\dots(6)$$

Value calculation:

$$V = C_{max} \dots\dots\dots (7)$$

RGB to HSB

$$H = \begin{cases} \left(\frac{G' - B'}{MAX - MIN} \right) / 6, & \text{if } R' = MAX \\ \left(2 + \frac{B' - R'}{MAX - MIN} \right) / 6, & \text{if } G' = MAX \dots\dots\dots(8) \\ \left(4 + \frac{R' - G'}{MAX - MIN} \right) / 6, & \text{if } B' = MAX \end{cases}$$

S (saturation) = 0, if R = G = B, otherwise $255 * (M - m) / (M + m)$, if $L < 128$, otherwise $255 * (M - m) / (511 - (M + m))$.

B (Brightness) = $(M + m) / 2$, where M is $\max(R, G, B)$ and m is $\min(R, G, B)$ [21]

5. Methodology and Results:

The practical stages of the proposed article are discussed in this section

1- Data collection and preprocessing

The data used to train and test the deep learning model is from publicly available dataset which is MIT-Adobe FiveK dataset , it provide various RGB images that are suitable for our method. MIT-Adobe FiveK dataset present 5000 digital images of dng format in different quality, resolution, and illumination conditions. The diversity of the illumination and quality of the images is the reason behind utilizing this dataset over others as shown in figure (1)

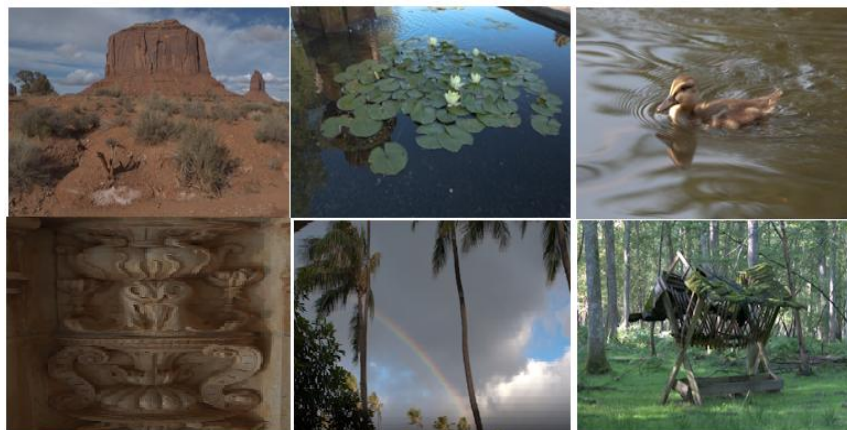


Figure 1 : MIT-Adobe FiveK dataset

2- Convert Color Space

In this section, we transform the color space from the RGB color space to multiple color spaces that show the mathematical characteristics of the color system. Figure 2 indicates digital image that is illustrated in different color space.

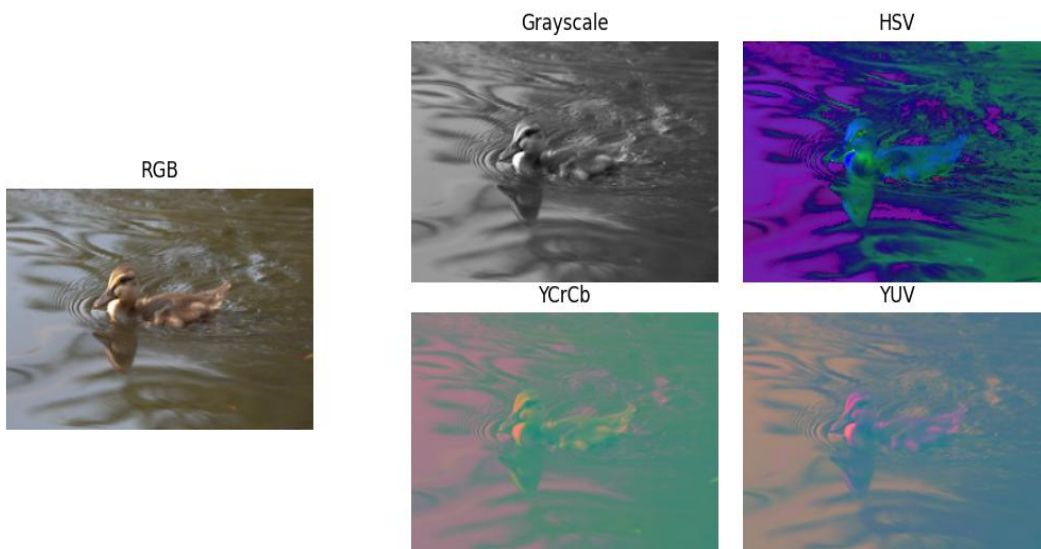


Figure 2: Image with different representation color space

3- Applying Deep Learning Model

Several deep learning techniques were implemented to reach the best model that can be applied in the digital image enhancement process, where the approach relied on the following models: VGG16, VGG19, CNN, U-Net, and Resnet50. The experiment showed that Resnet50 is the best model where ResNet50 is composed of multiple layers that involve the convolution layer, the pooling layer, the dropout layer and the fully connected layer. It is essentially a convolutional Neural Network (CNN) architecture with 50 convolutional layers (figure 3) and it is a variant of the residual network (ResNet) architecture which was developed to overcome the issue of vanishing gradient in deep neural networks by utilizing residual connections with skip connections that enable identity mapping and stable training of deeper models [21]. This process permits the network to skip some stages of computation and transfer data from lower layers to upper layers (figure 4), consequently leading to preserving crucial features during the training process. [22]

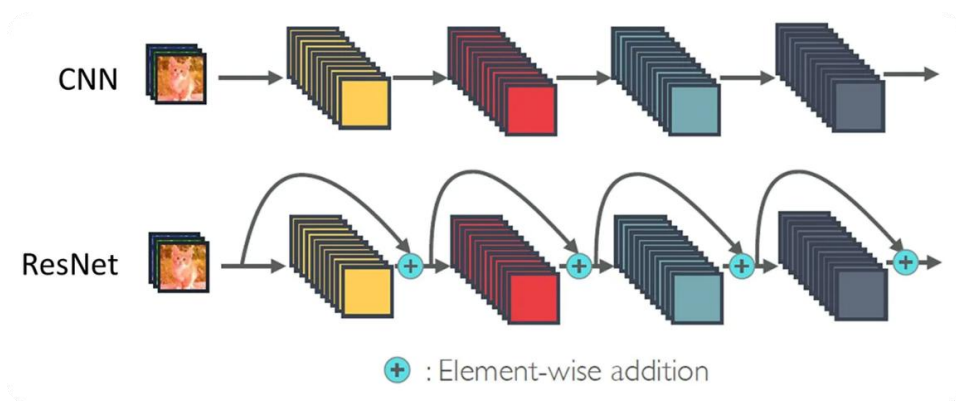


Figure 3: A comparison illustrating of CNN and ResNet

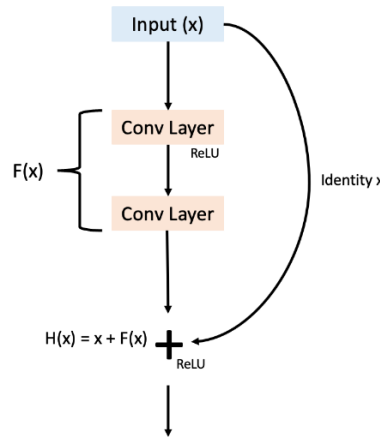


Figure 4 : Building Block of ResNet

Residual connections in each block permit the input to bypass intermediate layers and be added directly to the output, facilitating efficient gradient flow and enabling the training of very deep networks without degradation in performance. Most of the hidden layers use Batch normalization layers to stabilize the training process, while rectified linear unit (ReLU) activation functions add nonlinearity after each convolutional operation. The final layers consist of an average pooling layer followed by a fully connected layer with 1000 output class, suitable for classification tasks such as those in the ImageNet dataset. This design enables effective training of very deep networks and maintains high performance across a range of computer vision tasks[23].[24]

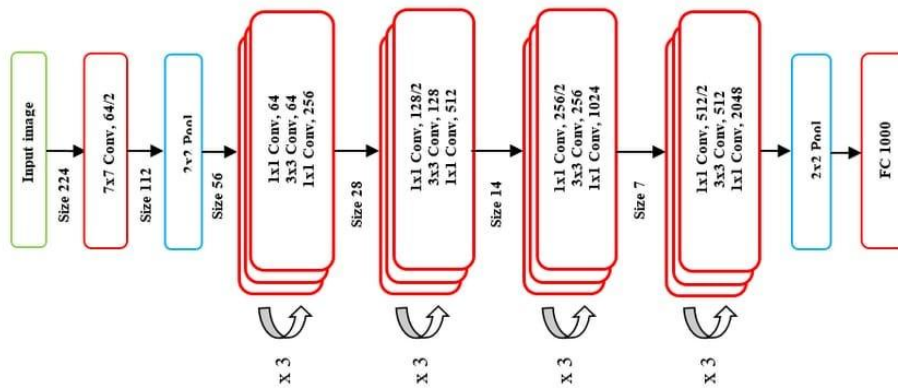


Figure 5 : diagram of Resnet Architecture

ResNet50 has been used as a transfer learning backbone for image classification tasks and medical imaging due to its high performance and versatility through various application fields. ResNet50 is considered a reference model in academic research and also practical learning applications, because of the ability to adapt with advanced learning modules to fit specific domain requirements while preserving strong generalization. Various improvement has been built on the core residual structure of ResNet50 such as integrated attention mechanism and domain-specific fine-tuning to enhance feature extraction and class imbalance handling.[25]

4- Evaluation metrics

The following measurement metrics were applied to evaluate the methods and find the final results.

1- Peak Signal-to-Noise Ratio (PSNR)

PSNR is widely applied in image processing (compression, enhancement, and reconstruction) as a quantitative measure of fidelity where higher PSNR value denotes better translation of the original image [2]. PSNR is derived from MSE as defined if the formula [26]:

$$PSNR = 10 \log_{10} \left(\frac{\max(I)^2}{MSE} \right) \dots\dots\dots (9)$$

Decibels (dB) is utilized to represent the measuring units of PSNR. PSNR is used as a baseline metric in experimental studies of image enhancement, image denoising and image reconstruction due to the simple scalar that make it easy to compare results across methods that shows how the processed image is noisy or distorted compared to the reference image[3].

When applying PSNR on the image, it may not interpret the perceptually of human eye. Also this metric shows sensitivity to small shifts or modifications in the illumination or contrast that could affect the results. Because PSNR is derived from MSE so it deals with pixel errors likewise, ignoring the structure, texture and contrast just like MSE does[27].

2- Structural Similarity Index Measure (SSIM)

The Structural Similarity Index Measure assesses perceptual similarity by encompassing the key components of the image: luminance, contrast, and structure, which can be defined as follows:[28]

$$L(X, Y) = \frac{2\mu_x\mu_y+C1}{\mu_x^2+\mu_y^2+C1} \dots\dots\dots (10)$$

$$C(X, Y) = \frac{2\sigma_x\sigma_y+C2}{\sigma_x^2+\sigma_y^2+C2} \dots\dots\dots (11)$$

$$S(X, Y) = \frac{\sigma_{xy}+C3}{\sigma_x\sigma_y+C3} \dots\dots\dots (12)$$

Here μ_x, μ_y are representing the means, and $\sigma_x\sigma_y$ are standard deviations, σ_{xy} the covariance between the images, and C1,C2,C3 are small constants[29].

$$SSIM = \frac{(2\mu_x\mu_y+C1)(2\sigma_{xy}+C2)}{(\mu_x^2+\mu_y^2+C1)(\sigma_x^2+\sigma_y^2+C2)} \dots\dots\dots (13)$$

SSIM is used in image processing to compare structure preservation and to detect structural distortions and contrast variation, where it is usually represented as a value [0,1] or [-1,1], and the value of 1 denotes identical images. Generally, SSIM is mostly addressed alongside PSNR to provide a more perceptually informed image of structural similarity and pixel error [4]. SSIM is vulnerable to saturate, which makes delicate differences difficult to identify. In computer vision tasks such as segmentation, object detection, or recognition, the preservation of structural similarity may not translate into better task performance, which necessitates applying additional evaluation metrics like Feature Similarity Index FSIM or Visual Information Fidelity [26].

4. Results and Discussions

- HSV Color Space Results analysis

The results of HSV color space reveal evident contrast in generalization across channels and the deep learning model, whereas the general pattern shows that applying the enhancement on the saturation channel (S) leads to a significant superiority compared to the other channels. Most deep learning models achieved high results

of both PSNR, and SSIM when performing on the S channel, with accuracy proceeds 95% in most cases, where the highest values are attained when this channel is merged with ResNet50 resulting in accuracy of 100% as shown in table 1. The high accuracy is mainly attributed to the saturation channel of the HSV color system which contains rich chromatic features and with the reduction of the adverse impact of the luminance variation that deep learning model can learn the crucial features of the image. In contrast, the findings illustrate that the combining of the value channel indicates lower scores of PSNR, SSIM, and accuracy, that reveals the channel sensitivity to noise and color alternations. CNN and VGG19 were more affected compared to other models, which reflects the limited ability to offset the lost structural information.

Table 1: HSV color space results

Color space&DeepLearning Model	PSNR	SSIM	ACCURACY
HSV &VGG16 SV	22.47	0.856	77.47%
HSV& VGG16 S	33.88	0.9842	99.02%
HSV & VGG16 V	22.47	0.856	80.49%
HSV& VGG19 SV	15.18	0.5567	42.55%
HSV&VGG19 S	30.47	0.953	95.63%
HSV&VGG19 V	15.01	0.551	41.15%
HSV&UNET SV	21.89	0.8261	75.16%
HSV&UNET S	31.49	0.973	98.03%
HSV&UNET V	21.71	0.8419	70.54%
HSV&RESNET50 SV	31.37	0.9586	97.40%
HSV& RESNET50 S	44.2	0.9952	100.00%
HSV& RESNET50 V	31.54	0.9587	97.32%
HSV&CNN SV	22.46	0.8411	77.84%
HSVCNNS	32.43	0.9769	98.54%
HSVCNNV	22.6	0.8577	76.13%

- HSB Color Space Results analysis

The results of the HSB color system indicated a behavioral resemblance to that obtained from the HSV color space, with a clear convergence to the various models in the evaluation metrics, especially when performing the enhancement on the saturation channel. The outcome has reflected that the deep learning depend on the S channel achieved a remarkable improvement in image quality that represented by the high values of PSNR and SSIM, alongside a high accuracy surpassed 98% as shown in Table 2.. The performance of the HSB color system presents a better perceptual characterization for brightness through the brightness channel, while preserving the saturation as an essential constituent to represent the color contrast. On the other hand, the reliance on the brightness channel or integrating it with the saturation channel reflect a degradation in the performance because the brightness channel displays the illumination intensity and it is sensitive to noise. In addition, the finding presented that deep learning models specifically ResNet50, led to leveraging the specifications of the HSB color space compared to other models, promoting the achievement of a high quality and stable outcomes.

Table 2: HSB color space results

Color space&DeepLearning Model	PSNR	SSIM	ACCURACY
HSBVGG16SB	22.47	0.856	77.47%

HSBVGG16S	33.31	0.9791	98.61%
HSBVGG16B	21.54	0.8323	76.14%
HSBVGG19SB	21.58	0.8337	76.53%
HSBVGG19S	33.24	0.9795	98.61%
HSBVGG19B	21.6	0.841	76.36%
HSBUNETSB	21.92	0.8243	74.32%
HSBUNETS	31.45	0.9792	98.02%
HSBUNETB	21.69	0.8411	70.41%
HSBRESNET50SB	31.37	0.9586	97.40%
HSBRESNET50S	44.2	0.9952	100.00%
HSBRESNET50V	31.54	0.9587	97.32%
HSBCNSB	21.91	0.8265	74.92%
HSBCNNS	31.54	0.9733	98.07%
HSBCNNB	21.88	0.8452	72.13%
HSBVGG16SB	22.47	0.856	77.47%

- HSI Color Space Results analysis

HSI color system has demonstrated a notable results particularly when relying on the saturation channel, where the highest values of PSNR, SSIM and accuracy were recorded compared to other color systems, where the accuracy surpassed 99%in multiple models as demonstrated in Table 3. The outperformance of the HSI color system can be related to the alignment with the human visual perception because it separates between the intensity and the chromatic information, enabling the model to concentrate on improving contrast and details without being affected by the variation of illumination. Meanwhile, the results demonstrate a significant degradation in all the evaluation metrics when relying on the Intensity channel, because this channel does not have enough chromatic information to support the enhancement effectively. Moreover, the models ReNet50 and U-Net gained more benefits from the HSI color system than VGG and CNN, because of their ability to conserve the features and utilize the color structure of the image.

Table 3: HSI color space results

Color space&DeepLearning Model	PSNR	SSIM	ACCURACY
HSIVGG16SI	18.78	0.7976	64.88%
HSIVGG16S	44.73	0.9966	99.97%
HSIVGG16I	18.85	0.8004	65.16%
HSIVGG19SI	18.4	0.7797	62.71%
HSIVGG19S	43.94	0.9963	99.96%
HSIVGG19I	18.48	0.783	62.99%
HSIUNETSI	28.04	0.9478	94.81%
HSIUNETS	37.64	0.9851	99.70%
HSIUNETI	19.29	0.8195	59.41%
HSIRESNET50SI	18.13	0.7908	64.50%

HSIRESNET50S	42.57	0.9951	99.90%
HSIRESNET50I	18.19	0.7953	64.69%
HSICNNSI	19.45	0.7915	61.04%
HSICNNS	38.02	0.9859	99.72%
HSICNNI	19.61	0.8064	61.04%

The findings indicate that the variation in the evaluation metrics (PSNR, SSIM, and Accuracy) is a result of the combined effect of both the chosen color representation and the deep learning model. The transformation to a nonlinear color space such as HSV, HSB, and HSI considered a principal step in the image enhancement process because it separates the chromatic components from illumination, this separation decline the impact of unwanted intensity variation which leads to more stable and reliable process of learning. The results emphasize that the achievement of effective image enhancement does not depend on the model complexity or depth but it necessitate a particular arrangement between the specified color system and the nature of the deep model architecture. Utilizing color channels informative structural information, alongside with the advanced networks capable of preserving the structural features, is the main factor to achieve the highest perceptual quality and optimal classification generalization.

The following figure 6 illustrates that the impact of the suggested method on the saturation layer which is common layer among all the mentioned color systems.

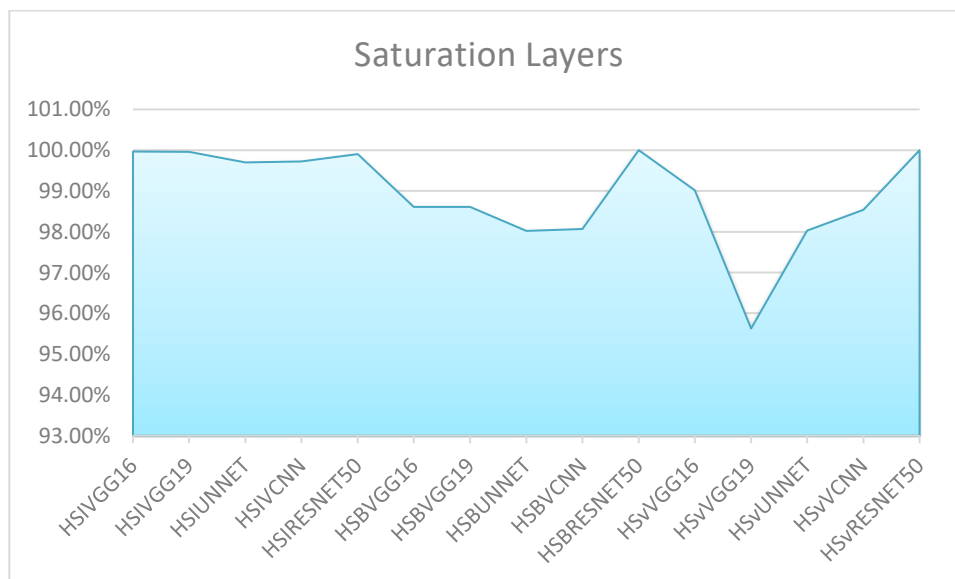


Figure 6: saturation Layer with Deep Learning Model

The results indicate that the ResNet50 Network was the best with this layer the reason is the architecture of this network is consistent with the work nature of digital image enhancement. Furthermore, the findings show that we can not manipulate the Hue layer, because any alternation in this layer means changing the color , because it represent the wavelength that leads to the impossibility of working with it.

5. Conclusions

From the obtained results and through discussing the findings that have been mentioned in the results section, that utilizing and depending on the deep learning models can significantly contribute in the enhancement of colored digital images. Moreover it is obvious that reliance on color systems that represent color space mathematically can leverage digital image color and contrast enhancement which is more beneficial than relying on the original color space of the digital image. Furthermore, multiple deep learning model has been trained and tested to conclude that the best model can be suitable to improve the digital image, where the finding from the ResNet50 model were the best among the other models that have been compared to in this article, the reason is the architecture of the ResNet50 which is feasible to the structure of the digital image indicating the outcome as following : PSNR = 44.2, and SSIM = 0.9952, and obtaining a high generalization during the training and testing process of the deep learning model.

References

- [1] A. S. Abdullah and K. I. Alsaif, "Computer vision system for backflip motion recognition in gymnastics based on deep learning," *J. AL-QADISIYAH COMPUT. SCI. MATH.*, vol. 15, no. 1, p. 150, 2023, doi: 10.29304/jqcm.2023.15.1.1162.
- [2] K. I. Alsaif and A. S. Abdullah, "Deep learning technique for gymnastics movements evaluation based on pose estimation," in *PROC. INT. CONF. FORTHCOMING NETW. SUSTAINABILITY AIOT ERA*, Cham, Switzerland: Springer, 2024, pp. 236–245, doi: 10.1007/978-3-031-62881-8_19.
- [3] A. S. Abdullah, W. K. Sleman, and M. Waleed, "Using cucumber plant leaves as a cover for hiding encrypted text," *J. PHYS.: CONF. SER.*, vol. 1804, no. 1, Art. no. 012004, 2021, doi: 10.1088/1742-6596/1804/1/012004.
- [4] M. Waleed, A. S. Abdullah, and S. R. Ahmed, "Classification of vegetative pests for cucumber plants using artificial neural networks," in *PROC. 3RD INT. CONF. ENG. TECHNOL. APPL. (IICETA)*, 2020, pp. 47–51, doi: 10.1109/IICETA50496.2020.9318890.
- [5] A. S. Abdullah, M. A. Abed, and I. Al-Barazanchi, "Improving face recognition by Elman neural network using curvelet transform and HSI color space," *PERIOD. ENG. NAT. SCI.*, vol. 7, no. 2, pp. 430–437, 2019, doi: 10.21533/pen.v7.i2.1333.
- [6] U. Khan ET AL., "A systematic literature review of machine learning and deep learning approaches for spectral image classification in agricultural applications," *COMPUT. MATER. CONTINUA*, vol. 78, no. 3, 2024, doi: 10.32604/cmc.2024.045101.
- [7] S. M. Mahdi and A. S. Abdullah, "Utilizing deep learning techniques to enhance digital image quality: A review paper," in *Proc. 2025 9th Int. Symp. Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 2025, pp. 1–6.
- [8] Z. Chen, K. Pawar, M. Ekanayake, C. Pain, S. Zhong, and G. F. Egan, "Deep learning for image enhancement and correction in magnetic resonance imaging—State-of-the-art and challenges," Australia, 2022.
- [9] M. Zhu, P. Pan, W. Chen, and Y. Yang, "EEMEFN: Low-light image enhancement via edge-enhanced multi-exposure fusion network," Australia, 2020.
- [10] M. Long, T. May, R. Liu, X. Fan, and Z. Luo, "Toward fast, flexible, and robust low-light image enhancement," China, 2022.
- [11] X. Zhao ET AL., "Development and quantitative assessment of deep learning-based image enhancement for optical coherence tomography," China, 2022.
- [12] S. H. Hwang, Y. J. Kim, J. B. Cho, K. G. Kim, and D. H. Nam, "Digital image enhancement using deep learning algorithm in 3D heads-up vitreoretinal surgery," Korea, 2025.
- [13] R. L. de Queiroz and K. M. Braun, "Color to gray and back: Color embedding into textured gray images," *IEEE TRANS. IMAGE PROCESS.*, vol. 15, no. 6, pp. 1464–1470, 2006.
- [14] A. J. S. Payne ET AL., "Chroma cartesian colour representations for plant image classification," in *PROC. IEEE/CVF INT. CONF. COMPUT. VIS. (ICCV)*, 2025, pp. 7128–7137.
- [15] W. Alkishri ET AL., "Fake face detection based on colour textual analysis using deep CNN," *J. INTERNET SERV. INF. SECUR.*, vol. 13, no. 3, pp. 143–155, 2023.
- [16] Y. Wu and Q. Li, "Watershed color image segmentation based on morphological gradient," *SENSORS*, vol. 22, no. 21, Art. no. 8202, 2022.
- [17] A. F. Cheshkova, "Hyperspectral image analysis techniques for plant disease detection," *VAVILOV J. GENET. BREED.*, vol. 26, no. 2, p. 202, 2022.
- [18] M. Muratbekova ET AL., "Color models in image processing: A review and experimental comparison," *ARXIV preprint arXiv:2510.00584*, 2025.
- [19] N. A. Ibraheem ET AL., "Understanding color models: A review," *ARPN J. SCI. TECHNOL.*, vol. 2, no. 3, pp. 265–275, 2012.
- [20] C. Wu, D. Wang, and K. Huang, "Enhancement of mine images based on HSV color space," *IEEE ACCESS*, vol. 12, pp. 72170–72186, 2024.
- [21] A. S. Abdullah, "Saturation component in HSB color space with image processing methods to enhance image segmentation," in *IOP CONF. SER.: MATER. SCI. ENG.*, vol. 928, no. 3, Art. no. 032082, 2020, doi: 10.1088/1757-899X/928/3/032082.
- [22] M. Shafiq and Z. Gu, "Deep residual learning for image recognition: A survey," *APPL. SCI.*, vol. 12, no. 17, Art. no. 8972, 2022.
- [23] F. Liu, X. Ren, Z. Zhang, X. Sun, and Y. Zou, "Rethinking skip connection with layer normalization in transformers and ResNets," *ARXIV PREPRINT ARXIV:2105.07205*, 2021.
- [24] L. H. Shehab, O. M. Fahmy, S. M. Gasser, and M. S. El-Mahallawy, "An efficient brain tumor image segmentation based on deep residual networks (ResNets)," *J. KING SAUD UNIV. ENG. SCI.*, vol. 33, no. 6, pp. 404–412, 2021.
- [25] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks," *PATTERN ANAL. APPL.*, vol. 24, no. 3, pp. 1207–1220, 2021.
- [26] S. A. Hicks ET AL., "On evaluation metrics for medical applications of artificial intelligence," *NATURE*, 2022, doi: 10.1038/s41598-022-09954-8.
- [27] J. Zhou, J. Zhang, J. Jia, and J. Liu, "SRGAN-based super-resolution reconstruction of power inspection images," *DISCOVER APPL. SCI.*, vol. 6, no. 12, Art. no. 639, 2024.
- [28] R. Archana and P. S. Eliahim Jeevaraj, "Deep learning models for digital image processing: A review," *ARTIF. INTELL. REV.*, vol. 57, no. 1, Art. no. 11, 2024.
- [29] A. S. Abdullah and Q. M. Hussein, "Using digital image as a cover of information hiding: Review paper," in *IOP CONF. SER.: MATER. SCI. ENG.*, vol. 928, no. 3, Art. no. 032085, 2020, doi: 10.1088/1757-899X/928/3/032085.