Improving the Quality of Biomedical Images Using Neural Networks *

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Abstract
The use of technologies to improve the quality of biomedical images allows to significantly increase the accuracy of classification and segmentation of data. The need for high resolution and clear contours of micro-objects is very high, as it allows to more clearly distinguish micro-objects and make a diagnosis more qualitatively. This paper presents a comparative analysis of convolutional neural network architectures to improve the quality of biomedical images and presents modified architectures, which increases the accuracy of further processing.

Keywords
mage quality, resolution, CNN

1. Introduction

Imaging techniques such as magnetic resonance imaging, computed tomography (CT) and ultrasound scanning play a key role in the detection and analysis of pathologies. In particular, the quality of the study is affected by the quality of cytological, histological, immunohistochemical images used in the diagnosis of breast cancer. However, the images obtained often have noise, artifacts and low resolution, which can complicate accurate diagnosis. Improving the quality of biomedical images is a critically important task that affects the efficiency of doctors and the accuracy of automated analysis systems.

Recent research in the field of artificial intelligence allows the use of advanced approaches to image processing and makes the process of quality improvement more versatile and perfect. Deep neural networks, such as convolutional neural networks (CNN) and transformers, demonstrate high efficiency in reducing noise, increasing contrast and restoring details in images. One of the disadvantages of using existing architectures of convolutional neural networks is the lack of universality regarding the type of images. For example, biomedical images are characterized by a significant level of noise and the absence of clear contours of the studied microobjects.

Scientists in the field of image processing pay significant attention to preprocessing and postprocessing, because this is a significant factor for further processing at a high level, for example,

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by convolutional neural networks. It is also worth noting the importance of high-quality contrast images for performing segmentation tasks using Unet tools.

The main goal of this work is to analyze existing architectures of convolutional neural networks for solving problems of improving image quality and developing modified architectures of convolutional neural networks.

- To solve the goal, it is necessary to implement the following tasks:
- Analyze existing approaches to improving image quality using machine learning

Develop modified architectures of convolutional neural networks for problems of improving the quality of biomedical images.

2. Literature review

In [1], a comparative analysis of the application of image analysis techniques is presented, in particular, the importance of ensuring high image quality is highlighted, which allows improving their processing. In [2], the authors investigate the assessment of image quality depending on the field of view (aFOV) and image acquisition time, which confirms the need to develop new approaches to improving image quality. In [3], the use of PROPELLER in MRI of the shoulder joint is presented and analyzed, reducing the influence of motion artifacts and improving image quality, which contributes to more accurate diagnosis. However, this method has a drawback - increased data acquisition time. In [4], deep learning methods for post-processing MRI images are considered to improve image quality and correct artifacts. The authors emphasize the importance of critical assessment of explanatory information and generalizability of deep learning algorithms in medical imaging, and also point out the current limitations in the application of artificial intelligence in MRI. The review aims to provide researchers in the field of MRI and related disciplines with important information for the development of methods for improving image quality. In [5], image quality assessment (IQA) is considered, which is important for the evaluation of new hardware and software tools, image acquisition methods, reconstruction algorithms and post-processing, in particular for medical images. The emphasis is on the application of IQA to such medical imaging methods as MRI, CT and ultrasound. In [6], the authors conducted a study that aims to compare and evaluate the quality of biopsy and cytology images obtained using two different devices: optical microscopes and scanners. The assessment is carried out in terms of contrast, color and staining of images, which are important criteria for the clinical application of biopsy and cytology images. According to the results of the study, scanners may have a slight advantage compared to microscopes, but the difference is minimal and not critical for practical application. A study [7] showed that the quality of optical coherence tomography images for the diagnosis and depth measurement of non-melanoma skin cancers may be dependent on the histological characteristics of the tumors themselves.

The work [8] is devoted to the analysis of image quality assessment (IQA) algorithms that aim to predict the perceived quality of images by humans. The authors tested 43 full-reference (FR) methods, seven combined FR methods (22 versions) and 14 no-reference (NR) methods on nine datasets rated by humans. An important aspect of the study is the use of various criteria to assess performance and statistical significance. The analysis emphasizes the importance of an expanded and more systematic approach to image quality assessment. Large-scale comparisons and new methods, such as the use of rating aggregation for FR fusion, can significantly improve the efficiency and accuracy of automated image quality assessment. The study [9] proposes a new architecture for image quality assessment based on transformers. The main idea is to use a transformer to process and compare images, including both a reference and a distorted image, with pre-extraction of perceptual features using a convolutional neural network (CNN). Experimental results show that the proposed model exhibits excellent performance on standard datasets for image quality assessment.

In [10], a new approach to image quality assessment (BIQA) is considered, which predicts human perception of quality without using a reference image. The main idea is to develop an automated multi-task learning scheme that uses auxiliary information from other tasks, such as scene classification and distortion type identification. In [11], a self-learning approach to image quality assessment without a reference sample (NR-IQA) is presented. The authors developed CONTRIQUE (CONTRastive Image QUality Evaluator)—a model that uses a convolutional neural network (CNN) to learn based on the prediction of the type and level of distortion in unlabeled image sets.

The main aspects of diagnosis based on immunohistochemical and cytological images are presented in [12]. Additionally, the importance of image preprocessing is presented. An adaptive method for preprocessing biomedical images is presented in [13].

3. Problem statement

The purpose of this article is to develop a convolutional neural network architecture to perform the task of improving the quality of immunohistochemical images for their further processing in classification, clustering, and segmentation tasks. To achieve this goal, it is necessary to perform the following tasks:

- analyze the immunohistochemical image dataset, select the training and validation samples;
- analyze existing neural network architectures to improve image quality;
- develop the proposed neural network architecture.

4. Dataset

The dataset selected was the immunohistochemical images dataset "IHCDBI" [14]. This dataset consists of immunohistochemical images of 4 categories and histology.

For the experiments, 500 images were selected, divided into training and test samples. The original images with a size of 3000 by 300 pixels were cut into portions with a size of 256 by 256 pixels. Examples of images are shown in Figure 1.

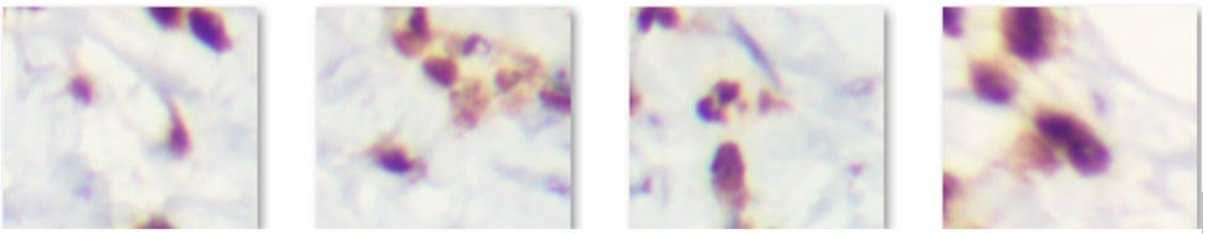

Figure 1: Image examples "IHCDBI"

5. Materials

The need for software solutions to improve the quality of immunohistochemical images arose due to the relatively poor image quality, the need for clear contours of microobjects and the absence of noise. Noise negatively affects image segmentation tasks in particular. An example of a noisy image using the salt-and-pepper algorithm is shown in Figure 2.

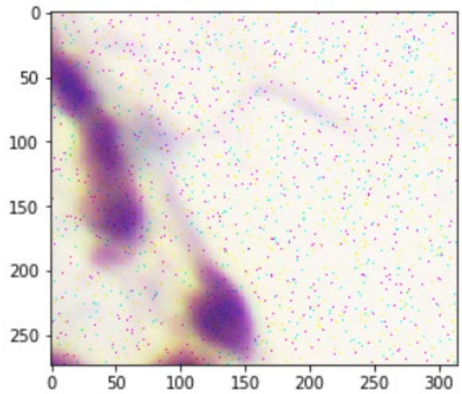

Figure 2: Examples of noisy images

The presence of noise negatively affects the quality of segmentation. Also, changes in contrast and brightness negatively affect segmentation.

In order to improve the quality of images, the following architectures of convolutional neural networks have been developed. The structure of the neural network is shown in Figure 3.

Layer (type)	Output Shape	Param #	Connected to
input_layer_3 (InputLayer)	(None, 256, 256, 3)	0	-
conv2d_17 (Conv2D)	(None, 128, 128, 64)	1,792	input_layer_3[0]…
leaky_re_lu_30 (LeakyReLU)	(None, 128, 128, 64)	0	conv2d_17[0][0]
conv2d_18 (Conv2D)	(None, 64, 64, 128)	73,856	leaky_re_lu_30[0…
leaky_re_lu_31 (LeakyReLU)	(None, 64, 64, 128)	0	conv2d_18[0][0]
conv2d_19 (Conv2D)	(None, 32, 32, 256)	295,168	leaky_re_lu_31[0…
batch_normalizatio… (BatchNormalizatio…	(None, 32, 32, 256)	1,024	conv2d_19[0][0]
leaky_re_lu_32 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalizat…
conv2d_20 (Conv2D)	(None, 16, 16, 512)	1,180,160	leaky_re_lu_32[0…
batch_normalizatio… (BatchNormalizatio…	(None, 16, 16, 512)	2,048	conv2d_20[0][0]
leaky_re_lu_33 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalizat…
conv2d_21 (Conv2D)	(None, 8, 8, 512)	6,554,112	leaky_re_lu_33[0…
batch_normalizatio… (BatchNormalizatio…	(None, 8, 8, 512)	2,048	conv2d_21[0][0]
leaky_re_lu_34 (LeakyReLU)	(None, 8, 8, 512)	0	batch_normalizat…
conv2d_transpose_15 (Conv2DTranspose)	(None, 16, 16, 512)	6,554,112	leaky_re_lu_34[0…
leaky_re_lu_35 (LeakyReLU)	(None, 16, 16, 512)	0	conv2d_transpose…
concatenate_15 (Concatenate)	(None, 16, 16, 1024)	0	leaky_re_lu_35[0… leaky_re_lu_33[0…
conv2d_transpose_16 (Conv2DTranspose)	(None, 32, 32, 256)	2,359,552	concatenate_15[0…
leaky_re_lu_36 (LeakyReLU)	(None, 32, 32, 256)	0	conv2d_transpose…
concatenate_16 (Concatenate)	(None, 32, 32, 512)	0	leaky_re_lu_36[0… leaky_re_lu_32[0…
conv2d_transpose_17 (Conv2DTranspose)	(None, 64, 64, 128)	589,952	concatenate_16[0…
leaky_re_lu_37 (LeakyReLU)	(None, 64, 64, 128)	0	conv2d_transpose…
concatenate_17 (Concatenate)	(None, 64, 64, 256)	0	leaky_re_lu_37[0… leaky_re_lu_31[0…
conv2d_transpose_18 (Conv2DTranspose)	(None, 128, 128, 64)	147,520	concatenate_17[0…
leaky_re_lu_38 (LeakyReLU)	(None, 128, 128, 64)	0	conv2d_transpose…
concatenate_18 (Concatenate)	(None, 128, 128, 128)	0	leaky_re_lu_38[0… leaky_re_lu_30[0…
conv2d_transpose_19 (Conv2DTranspose)	(None, 256, 256, 3)	3,459	concatenate_18[0…
leaky_re_lu_39 (LeakyReLU)	(None, 256, 256, 3)	0	conv2d_transpose…
concatenate_19 (Concatenate)	(None, 256, 256, 6)	0	leaky_re_lu_39[0… input_layer_3[0]…
conv2d_22 (Conv2D)	(None, 256, 256, 3)	75	concatenate_19[0…

Figure 3: Description of the neural network architecture

A visual representation of the layers of a convolutional neural network is shown in Figure 4

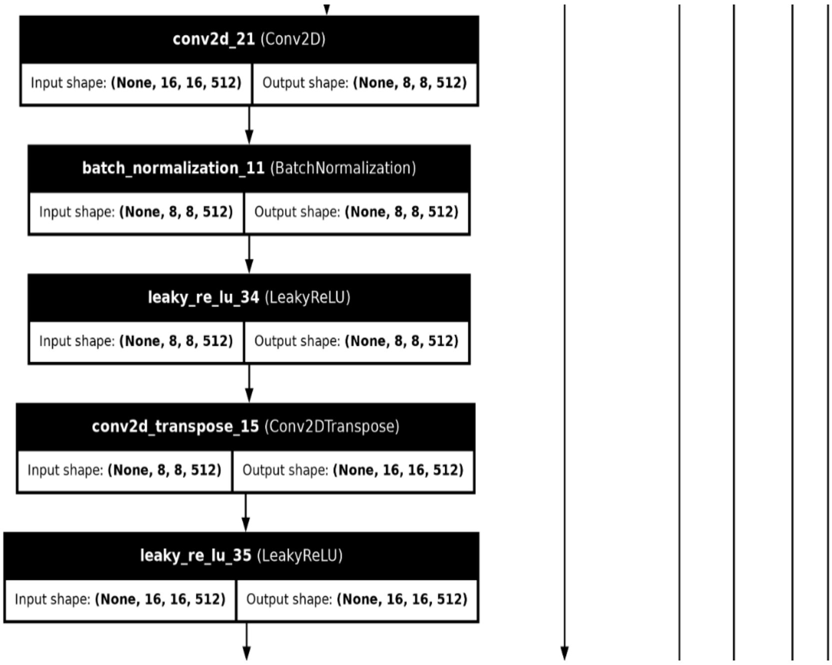

Figure 4 - Visual representation of the layers of a convolutional neural network

The image sample is divided into two parts: test and training. A feature of the Unet network and convolutional networks in general is the presence of repeating blocks.
Convolution block
Formally, the convolution process can be represented as follows:

$$I_{y,x} \times h = \sum_{i=-n_2}^{n_2} \sum_{i=-m_2}^{m_2} I(y-i, x-i) \cdot h(i,j)$$

where n_2 is half the filter height, m_2 is half the filter length, x is the pixel column position, y is the pixel row position, I_(y,x) is the input image, h is the convolution kernel.

6. Results

The results of the neural network are shown in Figure 3.

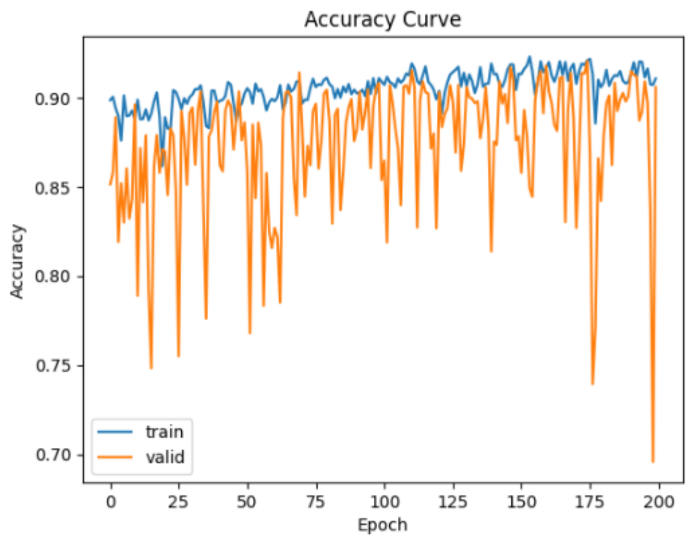

Figure 5: Results of the neural network operation

Figure 5 shows the results of processing an immunohistochemical image by a convolutional recurrent neural network. .

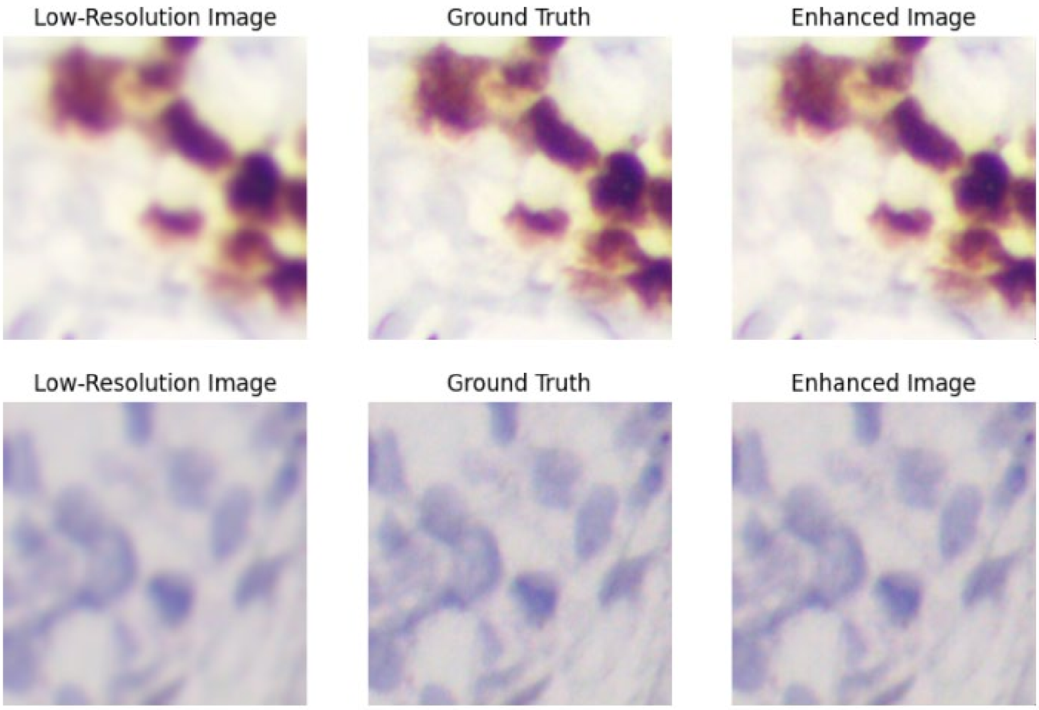

Figure 4: Results of immunohistochemical image processing by a convolutional recurrent neural network

Table 1

Comparative analysis of the results obtained

#	**accuracy**	**loss**	**val_accuracy**	**val_loss**
0	0.898655	0.005874	0.851424	0.009907
1	0.900496	0.005893	0.857951	0.006467
2	0.894160	0.005957	0.889043	0.006918
3	0.889853	0.006423	0.819108	0.011712
4	0.876054	0.006664	0.851936	0.008107

The analysis demonstrates minor differences between the accuracy of the training and test samples, which may indicate high quality training.

7. Conclusions

1. An analysis of modern approaches to improving image quality, in particular noise removal using computer vision and artificial intelligence algorithms, was carried out, which allowed us to highlight their advantages and disadvantages;
2. Based on the principles of developing convolutional neural networks, a modified neural network architecture was developed to improve image quality based on encoder and decoder technology;
3. Based on approaches to deploying software in cloud services, a CI/CD pipeline and a terraform script were developed to enable the deployment of software to improve the quality of immunohistochemical images, which allowed us to create the opportunity to deploy the project in various cloud services.
4. Analysis of the results obtained demonstrates that the accuracy of image restoration from noise is in the range of 85-90%.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

[1] Darwis, D., & Pamungkas, N. B. (2021). Comparison of least significant bit, pixel value differencing, and modulus function on steganography to measure image quality, storage capacity, and robustness. In Journal of Physics: Conference Series (Vol. 1751, No. 1, p. 012039). IOP Publishing. DOI 10.1088/1742-6596/1751/1/012039
[2] Rausch, I., Mannheim, J.G., Kupferschläger, J. et al. Image quality assessment along the one metre axial field-of-view of the total-body Biograph Vision Quadra PET/CT system for 18F-FDG. EJNMMI Phys 9, 87 (2022). https://doi.org/10.1186/s40658-022-00516-5
[3] Sobol, W. T. (2012). Recent advances in MRI technology: Implications for image quality and patient safety. Saudi Journal of Ophthalmology, 26(4), 393-399. https://doi.org/10.2214/AJR.10.606
[4] Chen, Z., Pawar, K., Ekanayake, M. et al. Deep Learning for Image Enhancement and Correction in Magnetic Resonance Imaging—State-of-the-Art and Challenges. J Digit Imaging 36, 204–230 (2023). https://doi.org/10.1007/s10278-022-00721-9
[5] Chow, L. S., & Paramesran, R. (2016). Review of medical image quality assessment. Biomedical signal processing and control, 27, 145-154. https://doi.org/10.1016/j.bspc.2016.02.006
[6] Redondo, R., Bueno, G., Cristóbal, G., Vidal, J., Deniz, O., Garcia-Rojo, M., ... & Gonzalez, J. (2012). Quality evaluation of microscopy and scanned histological images for diagnostic purposes. Micron, 43(2-3), 334-343. https://doi.org/10.1016/j.micron.2011.09.010
[7] Mogensen, M., Nürnberg, B. M., Thrane, L., Jørgensen, T. M., Andersen, P. E., & Jemec, G. B. (2011). How histological features of basal cell carcinomas influence image quality in optical coherence tomography. Journal of biophotonics, 4(7-8), 544-551. https://doi.org/10.1002/jbio.201100006
[8] S. Athar and Z. Wang, "A Comprehensive Performance Evaluation of Image Quality Assessment Algorithms," in IEEE Access, vol. 7, pp. 140030-140070, 2019, doi: 10.1109/ACCESS.2019.2943319.
[9] M. Cheon, S. -J. Yoon, B. Kang and J. Lee, "Perceptual Image Quality Assessment with Transformers," 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Nashville, TN, USA, 2021, pp. 433-442, doi: 10.1109/CVPRW53098.2021.00054.
[10] W. Zhang, G. Zhai, Y. Wei, X. Yang and K. Ma, "Blind Image Quality Assessment via Vision-Language Correspondence: A Multitask Learning Perspective," 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Vancouver, BC, Canada, 2023, pp. 14071-14081, doi: 10.1109/CVPR52729.2023.01352.
[11] P. C. Madhusudana, N. Birkbeck, Y. Wang, B. Adsumilli and A. C. Bovik, "Image Quality Assessment Using Contrastive Learning," in IEEE Transactions on Image Processing, vol. 31, pp. 4149-4161, 2022, doi: 10.1109/TIP.2022.3181496.

[12] Berezsky, Oleh, Oleh Pitsun, Grygoriy Melnyk, Tamara Datsko, Ivan Izonin, and Bohdan Derysh. 2023. "An Approach toward Automatic Specifics Diagnosis of Breast Cancer Based on an Immunohistochemical Image" Journal of Imaging 9, no. 1: 12. https://doi.org/10.3390/jimaging9010012
[13] O. Berezsky, O. Pitsun, B. Derish, K. Berezska, G. Melnyk and Y. Batko, "Adaptive Immunohistochemical Image Pre-processing Method," 2020 10th International Conference on Advanced Computer Information Technologies (ACIT), Deggendorf, Germany, 2020, pp. 820-823, doi: 10.1109/ACIT49673.2020.9208920.
[14] Database "IHCDBI Digital Immunohistochemical Image Database of Breast Cancer" / 10.05.2023 bulletin No. 76 dated 31.07.2023 // Copyright Registration Certificate Number 118979 https://iprop-ua.com/cr/0r6kml00/