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BRAIN MRI IMAGES ADAPTIVE DENOISING BY APPLYING NEURAL NETWORKS AND RANGE-BASED PARTITIONING

Introduction. *The denoising autoencoder model for enhancing the quality of T_1-weighted brain magnetic resonance imaging (MRI) images are considered.*

Methods. *This model utilized deep learning methods and incorporated additional components to improve performance and maintain structural integrity. The key elements included convolutional layers for feature extraction, batch normalization for stability, dropout for regularization, and a unique gradient constraint layer to preserve gradient smoothness.*

Results. *A specialized activation function classified pixel values based on predefined ranges, ensuring the model's adaptation to varying intensity levels in MRI data. The architecture consisted of an encoder-decoder structure with multiple steps of downsampling and concatenation, facilitating the reconstruction of high-quality images. The combination of these elements resulted in a robust model capable of reducing noise levels while preserving important anatomical details.*

Conclusions. *The implementation of this autoencoder model enhanced the clarity and diagnostic value of MRI scans, providing radiologists with improved tools for accurate assessment. The study was conducted using a comprehensive dataset of T_1-weighted brain MRI images.*

Keywords: *autoencoder, denoising, MRI Brain Images, deep learning, convolutional neural network, gradient constraint, image reconstruction, medical imaging, DICOM.*

Introduction

Medical imaging, particularly magnetic resonance imaging, holds significant importance in medical diagnostics and treatment. However, these images often contain noise or certain artifacts that can obscure fine details or introduce extraneous features, affecting diagnostic accuracy (Aja-Fernández, & Vegas Sánchez-Ferrero, 2016). Therefore, noise reduction methods are currently a relevant topic for enhancing the quality of MRI images, enabling more precise and reliable clinical assessments.

This research focuses on developing an advanced denoising autoencoder model specifically designed for T_1-weighted brain MRI images. The proposed model employs deep learning methodologies, particularly convolutional neural networks (CNNs), to effectively reduce noise while preserving essential anatomical features (Thakur et al., 2023). This approach integrates several innovations, with the primary one being gradient constraint levels, to ensure optimal performance. By distributing

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pixel values across specific ranges, the model adapts to varying intensity levels of MRI data, offering an improved and adaptive noise reduction process.

Методи

Dataset. The dataset used in this study includes T_1-weighted brain MRI images obtained from publicly available databases and anonymized clinical data sets. Each image in the dataset adheres to standard MRI protocols, ensuring consistency in terms of resolution, contrast, and anatomical coverage. The images are preprocessed to normalize intensity values.

Model architecture. At the core of the developed noise reduction system with an autoencoder model, developed with a encoder-decoder architecture as in most similar neural networks of noise reduction (Sliusarenko, Netreba, & Radchenko, 2023). The encoder extracts essential features from the noisy input images, while the decoder reconstructs the noise-free images. The model incorporates several advanced layers and techniques:

• Convolutional Layers: These layers apply convolutional filters to capture spatial features at various scales. The filters are trained to identify noise patterns and corresponding anatomical details.

• Batch Normalization: This technique normalizes the outputs of each convolutional layer, ensuring stable and efficient training by mitigating issues related to internal covariate shifts.

• Dropout Layers: Dropout regularization is used to prevent overfitting by randomly disabling a fraction of neurons during training, promoting model generalization.

• Gradient Constraint Layer: A unique addition to the model, this layer computes image gradients and enforces constraints to preserve smooth transitions and edges.

The gradient layer, as well as the method of dividing images at the network input, are new approaches to physical awareness, which have already begun to show themselves well in denoising tasks (Ghalambaz et al., 2024).

Evaluation metrics. The denoising performance is evaluated using several quantitative metrics:

• Peak Signal-to-Noise Ratio (PSNR): Measures the ratio between the maximum possible power of a signal and the power of corrupting noise, indicating the quality of the denoised image.

• Structural Similarity Index (SSIM): Assesses the similarity between the denoised image and the ground truth image in terms of luminance, contrast, and structure.

• Pearson Correlation Coefficient: Measures the linear correlation between the denoised image and the ground truth image.

• These metrics provide a comprehensive evaluation of the model's ability to reduce noise while preserving crucial anatomical details.

Results

Physics. Magnetic Resonance Imaging (MRI) utilizes powerful magnetic fields, radiofrequency (RF) pulses, and gradient fields to create detailed images of internal body

structures, including the brain (Cleary, & Guimarães, 2014). The fundamental principle is that hydrogen nuclei (protons) in body tissues, excited by the magnetic field and RF pulses, return to their equilibrium state, emitting an RF signal that is detected.

The patient is positioned within a magnetic field generated by a large magnet. This field aligns the hydrogen protons along the direction of the field.

Protons are excited using an RF pulse whose frequency corresponds to the Larmor frequency of the protons. This pulse causes the magnetic moments of the protons to tilt away from the main field.

After the RF pulse is turned off, the protons return to their equilibrium state, releasing energy in the form of RF signals. This process is known as relaxation and consists of two components: T_1 relaxation (longitudinal) and T_2 relaxation (transverse).

T_1-weighted images are obtained by measuring the signal during T_1 relaxation. Tissues with short T_1 times (e.g., fat) recover their longitudinal magnetization more quickly than tissues with long T_1 times (e.g., water). As a result, tissues with short T_1 appear brighter on the image, while tissues with long T_1 appear darker.

Distinguishing different tissues on MRI images is based on differences in T_1 and T_2 relaxation times and proton density. When choosing scan parameters such as repetition time (TR) and echo sequence time (TE), you can focus on different tissue types.

Short TR and short TE produce T_1-weighted images where the white matter is bright, and the CSF is dark.

The neural network layer formulas consider the physics of MRI, extracting and preserving important features corresponding to different brain tissues, normalizing data for learning stability, and imposing physical constraints on gradients to preserve signal properties. This provides efficient model training for denoising T_1-weighted MRI images.

We split the input images into pixel intensity ranges, and the network works with each range separately and assembles the output image.

Certain key elements of the network can be identified.

Input image X is normalized to the range [0, 1].

Convolutional layers perform the convolution operation, which is determined by the following formula:

$$Y_{i,j,k} = \sum_{m,n} W_{m,n,k} X_{i+m,j+n} + b_k.$$

Convolutional layers are used to extract image features that can correspond to physical properties of brain tissue, such as contrast and texture, and they extract spatial features that may correspond to the structure and texture of different brain tissues displayed in T_1 images.

The normalization layer performs the following operation:

$$\hat{X} = \frac{X - \mu}{\sqrt{\sigma^2 + \epsilon}}.$$

These layers consider the statistical properties of the data, which helps to stabilize the learning process, reducing the impact of variations in the data.

The gradient constraint layer imposes constraints on the gradients to account for the physical properties of the MRI signal:

$$Loss = \sum (\frac{\delta Y}{\delta X})^2 .$$

This imposes physical constraints on the gradients, ensuring that the physical properties of the MRI signal are considered when training the model.

At the end, decoding layers are used, which use reverse convolution and pooling operations with the aim of restoring the image to the original dimension

$$Y_{i,j,k} = \sum_{m,n} W'_{m,n,k} X'_{i+m,j+n} + b'_k ,$$

Evaluation metrics results. During training we used different levels of superimposed noise consisting of Gaussian and salt and pepper noise. A value of 5 % randomly damaged pixels with salt and percolation noise and a uniform Gaussian noise damage starting at 5 % and ending at 50 % are used throughout. To qualitatively evaluate image recovery, we have traditionally focused on PSNR and SSIM metrics (Mason et al., 2020). PSNR provides information about the overall image quality by measuring the average difference between the original and reconstructed image. PSNR provides information about the overall image quality by measuring the average difference between the original and reconstructed image.

SSIM. SSIM measures the structural similarity between two images (Mudeng, Kim, & Choe, 2022). This metric is because the human eye is more sensitive to changes in image structure than to changes in signal energy.

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

SSIM values range from –1 to 1, where 1 indicates perfect structural similarity, 0 indicates no similarity, and negative values indicate anticorrelation. SSIM considers three main components: luminance, contrast and structure, which makes this metric more complex and accurate compared to simple methods such as PSNR.

Figure 1 shows the change in the structural similarity index value with increasing noise level.

We can see that with an increase in the noise level, the value of SSIM decreases, however, evenly and gradually. At a relatively low level of noise (0–10 %), SSIM remains high (over 95 %), which means a high structural similarity between the original and the noisy image. At a very high level of noise (around 50 %), the SSIM drops to around 82 %, indicating a not very significant degradation of structural similarity even at this high level of noise.

PSNR. PSNR is used to measure the quality of image reconstruction. This is the ratio of the maximum possible signal power to the noise power, which affects the quality of its recovery.

$$PSNR = 20log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right),$$

where MSE (Mean Squared Error) is calculated as follows:

$$MSE = \frac{1}{mn} = \sum_{i=1}^{m}\sum_{j=1}^{n}[I(i,j) - K(i,j)]^2 .$$

PSNR is measured in decibels (dB). A higher PSNR value indicates a higher recovery quality, as it means a lower root mean square error.

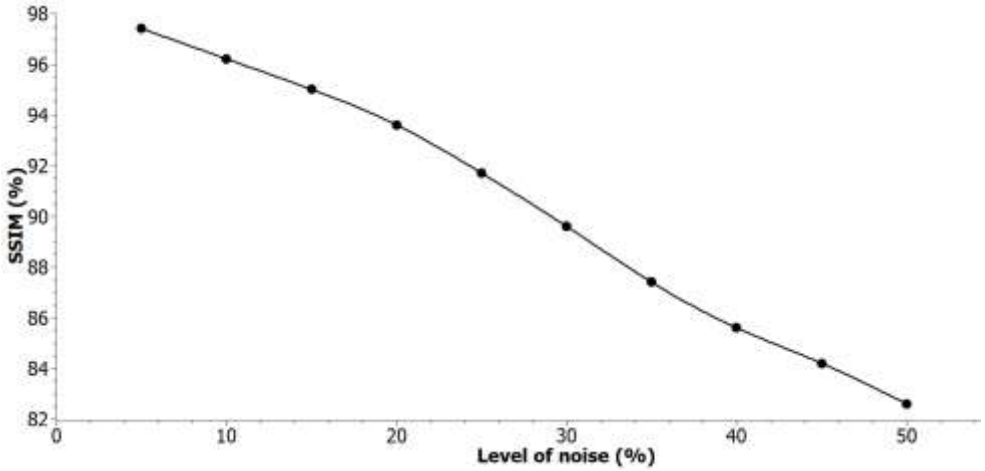


Fig. 1. Structural Similarity Index Measure Dependence of noise level

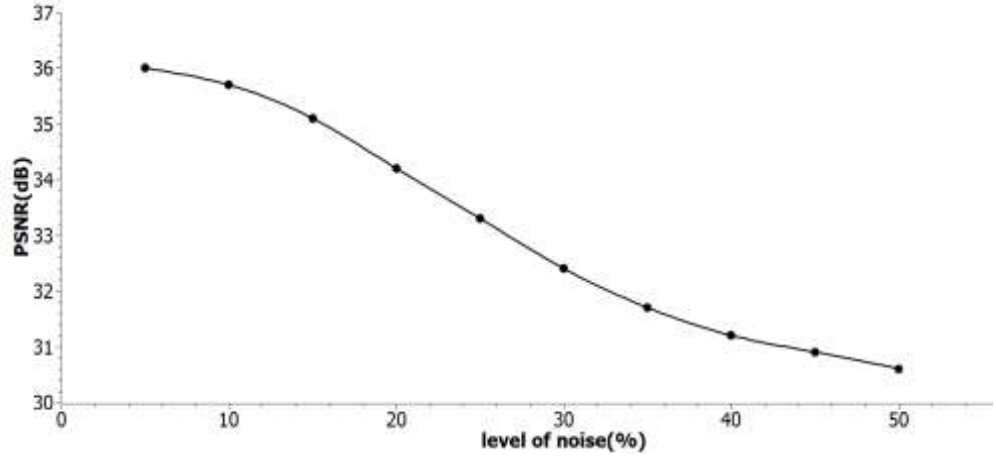


Fig. 2. Peak Signal-to Noise Ratio Dependence on noise level

The fig. 2, like the previous one, shows that as the noise level increases, the PSNR value decreases. At a low noise level (0–10 %), the PSNR remains high (over 35 dB), which confirms the previous quality assessment and at high noise levels, the PSNR drops to about 30 dB, which is still not a significant degradation, but no longer acceptable.

Pearson correlation. The Pearson Correlation Coefficient measures the linear relationship between two variables (Ding et al., 2022). Its values vary from –1 to 1, where

1 means a complete positive linear relationship (when one variable increases, the other also increases), –1 means a complete negative linear relationship (when one variable increases, the other decreases), 0 means no linear relationship between variables

The formula for calculating the Pearson correlation coefficient:

$$r = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{\left[n\sum x_i^2 - (\sum x_i)^2\right]\left[n\sum y_i^2 - (\sum y_i)^2\right]}}.$$

We can consider that the reconstructed image matches the original very well if there is a high correlation with values higher than 0.9. Additionally evaluating the restoration of images with a lot of noise, we obtained a Pearson correlation value higher than 99, which indicates a high linear correlation.

Discussion and conclusions

Developed a denoising autoencoder model to improve the quality of T_1-weighted brain MRI images. A deep learning model based on a classic autoencoder was used. The model was refined with additional layers for a more detailed restoration. A new approach is presented that combines several innovations, the main one being gradient constraint levels, to ensure optimal performance. By distributing the pixel values in certain ranges, the model adapts to the different intensity levels of the MRI data, offering an improved and adaptive noise reduction process.

Compared to other models that also give good results, our model uses a smaller data set, and other models also use non-classical DICOM images, which is very different from real clinical tasks.

It is shown that the use of this approach showed a high quality of denoising while maintaining good detail and leaving the original values of the gradients that were in the input image. We were able to obtain high recovery rates, as evidenced by SSIM values higher than 90 % for noise levels up to 20 %, and this was confirmed by an additional assessment of the peak signal-to-noise ratio, which also showed high value of about 35 decibels for this noise level. We believe that this model still has potential, but even such results are quite high given the new physics-based approach.

This approach has high potential because it is not based only on statistical features of images and noise, as most of the denoising models that have already been presented do. Our model uses physics as part of the denoising process. As further research, additional physical parameters can be considered, as well as the introduction of greater versatility into the model, to work not only with a certain type of MRI images.

Authors' contribution: Denys Sliusarenko – conceptualization, data curation, software, formal analysis, investigation, validation, visualization, writing – original draft, writing – review & editing; Andrii Netreba – supervision, funding acquisition.

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АДАПТИВНЕ ЗНЕШУМЛЕННЯ МРТ-ЗОБРАЖЕНЬ МОЗКУ З ВИКОРИСТАННЯМ НЕЙРОННИХ МЕРЕЖ ТА РОЗБИТТЯ НА ДІАПАЗОНИ

Вступ. ***Розроблено модель автоенкодера для знешумлення, призначену для покращення якості T_1-зважених магнітно-резонансних томографічних (МРТ) зображень мозку.***

Методи. ***Ця модель використовує методи глибокого навчання і містить додаткові компоненти для підвищення продуктивності та збереження структурної цілісності зображень. Ключовими елементами є згорткові шари для вилучення ознак, нормалізація пакетів для стабільності, dropout для регуляризації та унікальний шар градієнтних обмежень для збереження плавності градієнтів.***

Порівняно з іншими моделями, які також дають хороші результати, наша модель використовує менший набір даних. Інші моделі також застосовують некласичні DICOM-зображення, що сильно відрізняється від реальних клінічних завдань.

Результати. ***Спеціалізована функція активації класифікує значення пікселів на основі попередньо визначених діапазонів, забезпечуючи адаптацію моделі до різних рівнів інтенсивності в даних МРТ. Архітектура складається зі структури енкодер–декодер із кількома етапами пониження вибірки та конкатенації, що сприяло відтворенню високоякісних зображень. Поєднання цих елементів привело до створення надійної моделі, здатної знижувати рівні шуму, зберігаючи при цьому важливі анатомічні деталі. Одною з переваг розробленої моделі є використання DICOM-зображень замість класичного підходу з великими наборами jpeg-зображень, які через свою природу мають втрати і спотворення, що може призвести до неправильної діагностики.***

Висновки. ***Використання DICOM-зображень дає більш повну картину і містить усі необхідні деталі медичного зображення, які нам вдалося відновити після застосування різних рівнів шуму. Застосування цієї моделі автоенкодера покращило чіткість і діагностичну цінність МРТ-сканів, забезпечуючи радіологів кращими інструментами для точнішого оцінювання. Дослідження було проведено на основі комплексного набору даних T_1-зважених МРТ-зображень мозку.***

Ключові слова: ***автоенкодер, знешумлення, МРТ, глибоке навчання, горткова нейронна мережа, обмеження градієнта, відновлення зображення, медична візуалізація, DICOM.***

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