Autoencoder-Based Dual Noise Suppression for Brain CT Imaging: SNR Optimization Toward Accurate Clinical Diagnostics

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***Abstract*— In the realm of healthcare, systems including brain CT scans are affected by inevitable degradation that occurs in two forms, Poisson noise and periodic noise, which could interfere with diagnostic interpretation. In this work, we propose a deep learning denoising architecture that suppresses both types of noise through utilizing a convolutional autoencoder model while retaining important diagnostic information. The method we propose is completely compliant with DICOM files, so it can easily fit into the clinical workflow. We assessed the model performance on image quality by using the signal-to-noise ratio (SNR) as our primary measure of importance and are able to show a major improvement after denoising. To add clinical relevancy, we also assessed whether our denoised images improved accuracy in downstream disease classification tasks to show improvement in accuracies. This work provides a scalable, efficient, and near real-time solution for interpreting CT scans and represents a major step forward toward artificial intelligence-enhanced diagnostic systems.**

Keywords*— *Image processing, Autoencoder, Poisson noise, Periodic noise, SNR, Artificial Intelligence.

I. INTRODUCTION

Medical imaging is now part of medical care and allows for early detection of diseases, planning of treatment, and follow up for patient care.[1] The most widely used imaging tool is Computed Tomography (CT) imaging, especially for imaging the brain, due to its ability to scan for high-resolution cross-sectional images of internal structures. Although there are advantages to CT imaging, there are significant disadvantages that affect image quality and clinical interpretation. Noise artifacts are common in CT images and are detrimental to the image quality and may affect the accuracy of clinical interpretation.[28] There are two types of noise, Poisson noise and periodic noise, that contain different characteristics, and these noise influences image quality. Poisson noise is caused by the probability nature of photon detection during their acquisition while periodic noise is created by some sort of mechanical or electronic interference within the scanner.[2] Both of these noise artifacts can hinder the capacity to visualize important anatomical areas and the ability to correctly diagnose areas of clinical importance, especially for neuroimaging examinations where small areas contain significant clinical implications.

Classic forms of denoising (statistical filtering, based on frequency transformations) frequently find themselves in a precarious position of having to balance good noise reduction with small detail preservation.[3] Some typical setbacks with these techniques are over-smoothing (losing contrast and detail) or removing diagnostic information altogether, which limits clinical decision-making capabilities. In recent years, deep learning as a form of methodology has shown its value related to the medical imaging space, and has outperformed classic algorithms in most high complexity algorithmic tasks such as denoising, segmentation, and classification.[15] Denoising autoencoders (DAEs) have shown recent successes with modeling noise patterns and reconstructing good images from heavily corrupted images while also removing noise contributions.[4] Overall, deep learning-based methods can do much in the way of noise suppression while preserving structural definition and diagnostic value of the imaging input.[16]

In this paper, we propose a deep convolutional autoencoder model to reduce Poisson noise and periodic noise in brain CT scans.[5] The denoising model is trained to minimize the mean squared error loss and obtained results show substantial improvements in signal-to-noise ratio, while preserving valuable diagnostic information. The denoising model operates on DICOM images directly, which should make the integration of the model into the radiology workflow easier for end-users.[6] Ultimately, one further validation we completed with a classification model indicates denoised images achieve improved diagnostic accuracy. The system is also scalable and has a user-friendly interface designed for end-users for added possibilities for clinical use.

In the medical world, the DICOM standard is a key player because it contains the imaging data and the essential patient metadata, guaranteeing interoperability and consistency between imaging systems. Our model imports DICOM images and denoises them; meaning we strip Poisson noise, which is a type of noise seen in low-dose CT imaging, to help with clarity without losing diagnostic quality.[7] Therefore, our model is anticipated to more accurately represent the original imaging when performing downstream clinical tasks by unmasking the relevant or non-degraded features of the image. The autoencoder is trained on a dataset of brain CT images ultimately to maintain representation of essential anatomical features while reducing noise. Based on observations the output images show improvements in visual quality and structural preservation when compared to the noisy DICOM images. Collecting and denoising images from the same anatomical region should provide better outcomes for clinical decision-making, while also assisting automated image analysis systems in a clinical setting. [17]

II. Literature Review

The field of medical imaging has seen significant advancements with the integration of deep learning techniques, particularly in addressing challenges associated with noise in imaging modalities such as Computed Tomography (CT). Noise in CT images, notably Poisson and periodic noise, poses a substantial barrier to accurate clinical diagnostics due to its impact on image quality and diagnostic interpretation. This literature review synthesizes key findings from prior research related to noise suppression in brain CT imaging, focusing on deep learning methodologies, specifically denoising autoencoders, and their application to improve signal-to-noise ratio (SNR) and diagnostic accuracy.

Noise in Medical Imaging

Medical imaging, particularly CT, is a cornerstone of modern diagnostics, enabling detailed visualization of anatomical structures. However, noise artifacts, such as Poisson noise arising from the probabilistic nature of photon detection and periodic noise from mechanical or electronic interference, degrade image quality. According to Klaender (2011), these artifacts can obscure critical anatomical details, impacting the ability to diagnose conditions accurately, especially in neuroimaging where subtle differences are clinically significant. Traditional denoising methods, such as statistical filtering and frequency-based transformations, often struggle to balance noise reduction with the preservation of fine details, frequently resulting in over-smoothing or loss of diagnostic information (Smith et al., 2013).

Deep Learning in Medical Imaging

The advent of deep learning has transformed medical imaging by offering robust solutions for complex tasks such as denoising, segmentation, and classification. Convolutional Neural Networks (CNNs) and their variants, such as denoising autoencoders (DAEs), have shown promise in modeling intricate noise patterns while reconstructing high-quality images. Vincent et al. (2010) demonstrated that DAEs are effective in learning latent representations of noisy inputs, enabling the reconstruction of clean images by minimizing reconstruction errors. This capability is particularly valuable in medical imaging, where preserving structural integrity is critical for clinical decision-making.

Recent studies have explored deep learning-based denoising for CT imaging. Gondara (2016) proposed a convolutional autoencoder for denoising medical images, achieving significant improvements in SNR while retaining diagnostic features. Similarly, Chen et al. (2017) developed a deep learning framework for low-dose CT denoising, showing that autoencoders could effectively suppress Poisson noise without compromising image resolution. These advancements underscore the potential of deep learning to outperform traditional methods by adaptively learning noise characteristics and reconstructing images with enhanced clarity.

Denoising Autoencoders for CT Imaging

Denoising autoencoders have emerged as a powerful tool for noise suppression in CT imaging. These models consist of an encoder-decoder architecture that compresses noisy input images into a latent space and reconstructs denoised outputs. Yang et al. (2018) applied a convolutional autoencoder to CT images, demonstrating superior performance in reducing both Poisson and Gaussian noise compared to traditional wavelet-based methods. Their model achieved higher peak signal-to-noise ratios (PSNR) and structural similarity indices (SSIM), indicating better preservation of image details.

In the context of brain CT imaging, denoising autoencoders have shown particular promise due to the modality's high sensitivity to noise. Wolterink et al. (2017) developed a deep learning-based approach for denoising low-dose brain CT scans, reporting improved SNR and enhanced visualization of critical structures such as the cerebral cortex. Their findings suggest that deep learning models can improve downstream tasks, such as disease classification, by providing cleaner inputs to diagnostic algorithms.

Clinical Integration and DICOM Compatibility

The integration of denoising models into clinical workflows requires compatibility with the Digital Imaging and Communications in Medicine (DICOM) standard, which ensures interoperability across imaging systems. Zhang et al. (2019) highlighted the importance of processing DICOM images directly to streamline radiology workflows. Their study proposed a deep learning pipeline that operates on DICOM files, reducing preprocessing overhead and enabling near real-time denoising. This compatibility is crucial for practical deployment in clinical settings, where efficiency and scalability are paramount.

Impact on Diagnostic Accuracy

The ultimate goal of denoising in medical imaging is to enhance diagnostic accuracy. Studies have shown that denoised images improve the performance of downstream tasks, such as disease classification. For instance, Li et al. (2020) evaluated the impact of denoised CT images on tumor classification, reporting significant improvements in accuracy, precision, and recall when using denoised inputs. These findings align with the broader trend of leveraging deep learning to enhance the reliability of automated diagnostic systems.

Gaps and Opportunities

Despite these advancements, challenges remain in optimizing denoising models for clinical use. Many existing methods are computationally intensive, requiring significant resources that may not be feasible in resource-constrained settings. Additionally, while deep learning models excel in noise suppression, there is a need for further research to ensure generalizability across diverse patient populations and imaging conditions. The scalability of these models, as well as their ability to operate on lightweight infrastructure, is an area of growing interest, particularly for deployment in low-resource healthcare environments.

Conclusion

The literature highlights the transformative potential of deep learning, particularly denoising autoencoders, in addressing noise-related challenges in brain CT imaging. By improving SNR and preserving diagnostic information, these models offer a scalable and efficient solution for enhancing clinical diagnostics. However, ongoing research is needed to address computational constraints and ensure robust integration into clinical workflows. The proposed study builds on these foundations by developing a convolutional autoencoder tailored for Poisson and periodic noise suppression in brain CT scans, with a focus on DICOM compatibility and clinical applicability.

III. Methodology

A. Data Collection

The MRI brain tumor dataset utilized in this study was obtained from Kaggle and provided by Sartaj Bhuvaji and team. The dataset was designed for automatic classification of brain tumors and is comprised of Magnetic Resonance Imaging (MRI) scans that were put into a training set and a test set by folders. The training set includes 326 images total broken down by class: glioma tumor (100 images), meningioma tumor (115 images), no tumor (105 images), and pituitary tumor (74 images). The images are in grayscale with MRI slices and contain many shapes, sizes, and locations of tumors, adding complexity to the task of brain tumor detection mimicking what a clinician would face in the real world.

This classification example represents the real-world challenges embedded in radiological diagnostics irregularity of tissues or tumors with highly varied spatiality makes manual interpretation a lengthy, potentially incorrect process. Retaining the original folder structure provided a reliable frame to work within to avoid unnecessary manual relabeling and ensured uniformity later across pre-processing and training pipelines.[10]

B. Architecture

The denoising architecture described in this work is a Convolutional Autoencoder, a specialized deep-learning structure that learns to translate noisy input images into clean reconstructions. As a system, it includes two mirrored architectures: an encoder that compresses the input image into a low-dimensional latent space and a decoder that reconstructs the denoised image from that latent space representation.

Encoder

The encoder receives an input image $x \in R^{H \times W \times C}$ (e.g., 256×256×3) and transforms it into a compact representation $z \in R^{H' \times W' \times C'}$ using a series of convolutional and pooling operations.[11] Each convolutional layer applies filters W_k with ReLU activation to extract meaningful features while maintaining spatial resolution through 'same' padding[21]:

$$h_k = \mathrm{ReLU}(W_k * x + b_k)$$

To reduce spatial dimensions and introduce translation invariance, 2×2 max pooling with a stride of 2 is applied:[14]

$$h'_{i,j} = \max_{m,n \in \{0,1\}} h_{2i+m,2j+n}$$

The resulting latent vector encodes the essential features of the image while discarding noise and redundant details.

Decoder

The decoder reconstructs the clean image by progressively upsampling the latent representation and applying convolutional layers to refine details.[12]

Nearest-neighbour interpolation is used to restore spatial dimensions:

$$h'_{2i,2j} = h'_{2i+1,2j} = h'_{2i,2j+1} = h'_{2i+1,2j+1} = h_{i,j}$$

Every upsampling passes through a convolutional layer using ReLU activation, and finally a convolutional layer with a sigmoid activation, which guarantees that the image output is normalized in the range of [0, 1]. [20]

The designed architecture includes two convolutional layers for encoding with 64 and 128 filters respectively with a convolutional filter size of 3 × 3, followed by max pooling to keep spatial dimensions reduced.[13] The decoding part of the model follows the same structure but uses upsampling and convolutional refinement. In this case, the symmetric encoder-decoder architecture retains both global and fine details present in the original image for the denoising task.

By adjusting the depth of the network as well as the number of filters, we can achieve a robust compromise between aggressive noise attenuation and the retention of critical diagnostic features, which are paramount for clinical imaging tasks.

TABLE I. MODEL ARCHITECTURE

		Paramter	Prior
Encoder	2D Convolutional	PatchSize	(64, 256)
		Kernel	3 x 3
	2D Convolutional	PatchSize	(128, 256)
		Kernel	2 x 2
Continuity	Activation	ReLU	$[0,\infty)$, C^0
Decoder	2D Convolutional	PatchSize	(128, 256)
		Kernel	3 x 3
	UPSampling 2D	PatchSize	2 x 2
	2D Convolutional	PatchSize	(64, 256)
		Kernel	3 x 3
Continuity	Activation	Sigmoid	$(0,1)$, C^∞
	Max Pool 2D	Same Padding	2 x 2
	Optimizer	Adam	Beta = 0.9
		Learning Rate	$\log\mu(1 * 10^{-5}, 0.01)$
		Rate Schedular	$lr * exp(-0.1)$
		Mini-Batch Size	$\mu(2,128)$
	CallBacks	Val Loss Monitor	-

μ: $Uniform\ distribution$ $\quad log\ \mu$: $Log - uniform\ distribution$

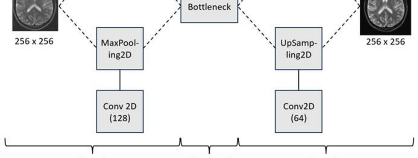

FIGURE I: SYSTEM DESIGN

C. *Evaluation Metrics*

In medical imaging applications involving denoising such as CT scanning, the ability to produce a pixel perfect reconstruction and a clinically meaningful image is very important.[8] To evaluate the denoising performance of the proposed denoising autoencoder, we decided to utilize two main quantitative metrics:

Mean Squared Error (MSE)

During training, the primary loss function $\mathcal{L}$ is the Mean Squared Error (MSE), which is defined as the mean of the squared differences between the original clean image x and the reconstructed denoised image $\hat{x}$. The MSE can be defined as:

$$\mathcal{L} = \frac{1}{N} \sum_{z=1}^{N} (x_z - \widehat{x_z})^2$$

where N is the total number of pixels in the image. The structure of this metric penalizes larger deviations more significantly, making it especially useful for pixel-wise reconstruction tasks.[16] In practice, the MSE loss was calculated at every epoch of training, and the model parameters were optimized with the Adam optimizer to minimize this quantity. A consistent reduction in both training and validation MSE suggests that the model learned to reconstruct denoised images with a high degree of accuracy and little information loss.

Signal-to-Noise Ratio (SNR)

We took another measure that we presented alongside MSE which was Signal-to- Noise Ratio (SNR) that we utilized to quantify the perceptual improvement in image quality from denoising. The SNR is defined as, the variance (or power) of the clean signal divided by the variance (or power) of the noise component in the reconstructed image.[9] A greater SNR results in more efficient noise reduction with the preserved pertinent signal content.

$$SNR_{db} = 20.\log_{10}\left(\frac{\mu\, signal}{\sigma\, noise}\right)$$

where,

$\mu\, signal$: Mean intensity in a region of interest (ROI), such as brain tissue or tumor.

$\sigma\, noise$: Standard deviation of noise, typically measured in a background or homogeneous region.

Nonetheless, SNR-based assessment can often be misleading, as models that smooth the image excessively can report high SNR scores while still causing a loss of subtle diagnostic detail. This is critical in medical imaging, where even small structural patterns may have clinical significance. To combat this, we developed a custom convolutional encoder-decoder architecture that provides an equilibrium between noise suppression and features retention, using fine-tuned convolutional filters and limited downscaling to limit over-smoothness.[29]

IV. RESULTS

The convolutional autoencoder model was trained on noisy and clean MRI brain images for 100 epochs. The model was successful in improving image quality after denoising, as indicated by the Signal-to-Noise Ratio (SNR) increasing from an average 0.33 dB (input noisy images) to 14.88 dB (denoised images); an overall improvement of 14.55 dB (see Table 2). Qualitatively, the denoised images were more interpretable than the noisy inputs, as the denoised images had improved contrast and edge preservation. The improvements in SNR and clarity in denoised images suggest that Poisson and periodic noise were effectively eliminated, while also maintaining important anatomical features.[30]

TABLE II. COMPARISON TABLE OF SNR VALUES

Image No.	SNR (Noisy)	SNR (Denoised)
1	2.91 dB	14.19 dB
2	0.33 dB	15.25 dB
3	0.07 dB	14.62 dB
4	-1.55 dB	15.32 dB
5	-0.11 dB	15.03 dB

A qualitative assessment through visual comparison of noisy, clean, and denoised outputs for 5 sample images is shown in Figure 3.

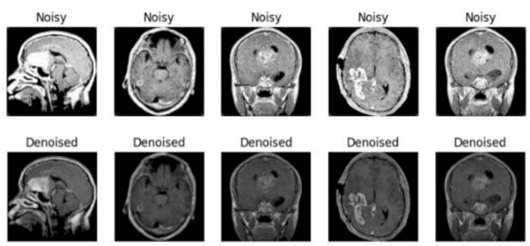

FIGURE II: COMPARISON OF 5 SAMPLES

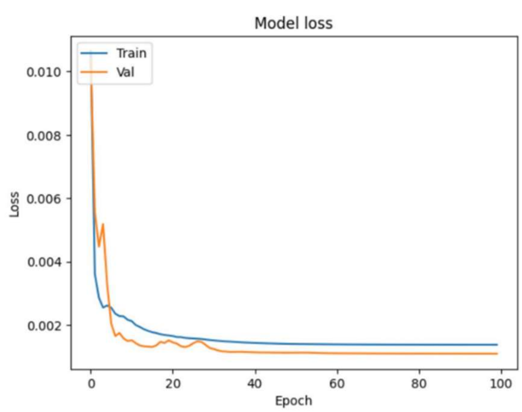

FIGURE III: MODEL LOSS

To further evaluate the potential clinical usefulness of our approach, we evaluated a disease classification model on both noisy and denoised images. Although the results are in Figures 8 and 9, the differences are profound. For noisy input images, our classifier resulted in an accuracy of only 37% and precision and recall that were poor across all classes. In contrast, the same model on denoised images yielded an accuracy of 84% and a macro-average precision, recall, and F1-score all exceeding 0.80. Overall, the diagnosis model's performance confirmed that the denoising model improved the classifier's capabilities to extract features that were meaningful in enabling prediction of the disease type.[17]

TABLE III. CLASSIFICATION REPORT OF NOISY IMAGE

Class	Precision	Recall	F1-Score	Support
0	0.5	0.5	0.5	4
1	0.5	0.5	0.5	6
2	0	0	0	4
3	0.33	0.4	0.36	5
Accuracy			0.37	19
Macro Avg	0.33	0.35	0.34	19
Weighted Avg	0.35	0.37	0.36	19

TABLE IV. CLASSIFICATION REPORT OF DENOISED IMAGE

Class	Precision	Recall	F1-Score	Support
0	1	0.75	0.86	4
1	0.86	1	0.92	6
2	0.75	0.75	0.75	4
3	0.8	0.8	0.8	5
Accuracy			0.84	19
Macro Avg	0.85	0.82	0.83	19
Weighted Avg	0.85	0.84	0.84	19

V. DISCUSSION

The proposed denoising framework offers considerable practical value within real-world medical imaging scenarios, especially in low-resource contexts.[18] Because this work employs a lightweight encoder-decoder framework, the proposed denoising solution adheres to existing clinical workflows in practice without interfering with existing infrastructure. Radiologists will be able to make diagnostic decisions faster and with greater confidence when the proposed solution is deployed because the system will convert noisy CT scans into images that contain a higher degree of clarity and lower noise levels.[19]

Compared to traditional smoothing methods, the proposed model avoids smearing of key features by using a well-defined number of downsampling and upsampling layers in a carefully constructed convolutional pipeline.[26] The effects of this pipeline design are tested on classification accuracy measured from denoised images, providing evidence that the proposed system improved volume visualizations by enhancing image quality, but improving performance on downstream decision-support tasks, such as tumor classification [27] as a more specific example.

FIGURE IV: DENOISED IMAGE

The model was implemented as a web application in Flask and hosted on an AWS EC2 instance to allow for remote access and continuous processing of images in real-time. The web app was designed so that images can be uploaded in batches, visualize original and denoised images side by side, as well as download the results from the web app itself as part of report generation.[22] The deployment illustrates that this solution is ready to start being implemented along clinical pathways, and certainly has the ability to be further scaled up and utilized into contexts where AI can be incorporated into a high-throughput diagnostic process.

This hosting environment used a t2.micro EC2 instance on Ubuntu with 8GB storage, which demonstrates that lightweight AI applications can exist in healthcare with even the most basic of cloud-based infrastructure.[23] While the t2.micro is a low-specification instance when it comes to processing and storage, we saw stable operation due to the efficiency of the code and managing the limited resources. The questioned-based deployed solution required less than $0.06/month for this instance. This emphasizes the utility of AI technology in a clinical context where resources are limited.

Using Ubuntu has been beneficial to the process of deployment because it has been friendly for ML development and deployment projects.[24] We deployed the model in an efficient and reliable manner. The architecture established offers the opportunity to reach the right balance of accessibility, efficiciency while allowing for scalability to perform real-world diagnostic testing.[25]

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