applied sciences

MDPI

Communication

Using Compressed JPEG and JPEG2000 Medical Images in Deep Learning: A Review

Ilona Anna Urbaniak

Department of Computer Science, Faculty of Computer Science and Telecommunications, Cracow University of Technology, ul. Warszawska 24, 31-155 Cracow, Poland; ilona.urbaniak@pk.edu.pl

Abstract: Machine Learning (ML), particularly Deep Learning (DL), has become increasingly integral to medical imaging, significantly enhancing diagnostic processes and treatment planning. By leveraging extensive datasets and advanced algorithms, ML models can analyze medical images with exceptional precision. However, their effectiveness depends on large datasets, which require extended training times for accurate predictions. With the rapid increase in data volume due to advancements in medical imaging technology, managing the data has become increasingly challenging. Consequently, irreversible compression of medical images has become essential for efficiently handling the substantial volume of data. Extensive research has established recommended compression ratios tailored to specific anatomies and imaging modalities, and these guidelines have been widely endorsed by government bodies and professional organizations globally. This work investigates the effects of irreversible compression on DL models by reviewing the relevant literature. It is crucial to understand how DL models respond to image compression degradations, particularly those introduced by JPEG and JPEG2000—both of which are the only permissible irreversible compression techniques in the most commonly used medical image format—the Digital Imaging and Communications in Medicine (DICOM) standard. This study provides insights into how DL models react to such degradations, focusing on the loss of high-frequency content and its implications for diagnostic interpretation. The findings suggest that while existing studies offer valuable insights, future research should systematically explore varying compression levels based on modality and anatomy, and consider developing strategies for integrating compressed images into DL model training for medical image analysis.

Keywords: medical image quality; deep learning; machine learning; DICOM image compression; medical images; irreversible compression

Citation: Urbaniak, I.A. Using Compressed JPEG and JPEG2000 Medical Images in Deep Learning: A Review. *Appl. Sci.* **2024**, *14*, 10524. https://doi.org/10.3390/app142210524

Academic Editor: Fabio La Foresta

Received: 16 August 2024
Revised: 29 October 2024
Accepted: 12 November 2024
Published: 15 November 2024

1. Introduction

The amount of data generated from patient medical records has increased rapidly due to advancements in medical imaging technology, creating a need for effective management strategies for storing historical patient information. To address this challenge, researchers and radiologists have undertaken extensive studies to establish acceptable compression ratios for irreversible compression methods, which permanently discard some image data while preserving diagnostic quality. These investigations have demonstrated that irreversible compression can be applied to medical images without compromising diagnostic integrity, thereby ensuring the retention of critical details essential for accurate diagnosis [1–7]. The focus has been on various compression algorithms, including JPEG and JPEG2000, across multiple medical imaging modalities, such as Computed Radiography (CR), Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, Angiography, Mammography, and Dental imaging.

The existing studies have led to the development of guidelines for using irreversible compression for the storage, retrieval, and transmission of medical image data and are supported in the DICOM [8] standard, technically allowing the use of acceptable compression ratios for different imaging modalities and anatomical regions in the protocol [9]. Furthermore, irreversible compression for medical images supported by numerous published research findings, case studies, and reviews has received regulatory approval from government bodies and professional organizations worldwide, including as follows:

- The European Society of Radiology (ESR), which offers guidelines for image compression and data management in Europe, emphasizing the need to maintain high diagnostic quality while managing large volumes of imaging data [6].
- The Canadian Association of Radiologists (CAR), which provides guidelines for image compression and image quality management in Canada. These guidelines include recommended compression ratios based on modality and anatomy [10].
- The Royal Australian and New Zealand College of Radiologists (RANZCR), which recommends the use of lossless compression where possible and lossy compression according to the recommended compression ratios provided by CAR [11].
- The American College of Radiology (ACR), which does not provide specific compression ratios or algorithms; however, it is the responsibility of the qualified physician to ensure diagnostic accuracy and maintain image integrity across various imaging modalities when using irreversible compression [12].
- The Royal College of Radiologists (RCR) in the United Kingdom, which has established guidelines for employing lossy compression in clinical settings. They provide recommendations for compression ratios for primary diagnosis, depending on the imaging modality [13].
- The German Röntgen Society (DRG), which has issued guidelines for the lossy compression of digital radiological images, including recommended compression ratios based on modality [14].

Although there is a consensus on setting some limits for irreversible compression of medical images, a unified standard for acceptable compression ratios has not been established. Table 1 provides a summary of compression ratio recommendations by anatomy and modality as published by CAR, DRG, and RCR [6]. However, it is critical to emphasize that the guidelines also suggest that the final decision regarding the use of irreversible compression, its parameters, and its impact on diagnostic quality should be made at the discretion of a qualified physician who can assess the diagnostic quality of a compressed image. Thus, while the recommended compression ratios provide a general guideline for preserving diagnostic image quality, radiologists must evaluate each case individually. They need to consider specific medical contexts, imaging modalities, characteristics of the pathology and anatomy, and clinical requirements to ensure that the image quality remains adequate for accurate diagnosis. The scientific evidence supporting the use of irreversible compression not only aids in managing long-term storage requirements and the transmission of images but also ensures that the quality of patient care is not compromised. Radiologists and healthcare hardware and software providers around the world rely on these standards to maintain a balance between efficient data storage and the need for high-quality diagnostic images.

Irreversible compression reduces file size by eliminating high-frequency content from images. This high-frequency content includes fine details and subtle variations that may not be immediately visible to the human eye but can significantly affect image quality. While the reduction in file size helps decrease storage and transmission costs, it irreversibly leads to some loss of detail, which could potentially impact the diagnostic fidelity of the images in certain cases.

While the diagnostic quality of compressed medical images has been extensively studied and documented in the scientific literature, the effects of irreversible compression on the training and performance of ML models remain underexplored. This is particularly significant, as understanding these effects is crucial for developing reliable ML-based tools for medical image analysis. High-frequency content, which is often removed by irreversible compression, could be significant for ML models as it includes fine details that might enhance model performance. Conversely, this high-frequency content can also correspond to noise, and its removal might result in better quality data that represent only the relevant image information.

Table 1. Summary of Medically Accepted Compression Ratios by Modality and Region [6].

Modality	Compression Ratio Range	Regions with Highest Accepted Compression	Regions with Lowest Accepted Compression
CR (chest, skeletal, body)	10:1–30:1	Canada (30:1)	UK, Germany (10:1)
CR (pediatric)	Up to 30:1	Canada	Not available for UK, Germany
CR (mammography)	15:1–25:1	Canada (25:1)	Germany (15:1), UK (20:1)
CT (head)	5:1–12:1	Canada (12:1)	UK, Germany (5:1)
CT (skeleton/chest/lung)	5:1–15:1	Canada (15:1)	UK (5:1)
CT (body)	10:1–15:1	Canada, Germany (15:1)	Not available for UK
CT (angio, pediatric)	Up to 15:1	Canada	Not available for UK, Germany
MR	5:1–24:1	Canada (24:1)	Germany (7:1), UK (5:1)
NM	Up to 11:1	Canada	Not available for UK, Germany
US	10:1–12:1	Canada	Not available for Germany
XA, XRF	6:1	Germany	Not available for UK, Canada

This work reviews the scientific literature to investigate whether irreversible compression of medical images affects the accuracy of ML models. The study aims to determine how ML models respond to image compression degradations. It addresses this problem by presenting scientific knowledge on the degradations caused by JPEG and JPEG2000 compression methods and examining how ML models react to these degradations in the context of medical image analysis.

The study aims to provide a comprehensive analysis by:

- Analyzing JPEG and JPEG2000 compression impacts on medical image quality: focusing on the specific degradations introduced by these compression methods, such as the loss of high-frequency content, and exploring their potential implications for diagnostic human interpretation.
- Investigating the performance of DL models on compressed medical images by reviewing the existing literature on the evaluation of various ML models using both compressed and uncompressed medical images.
- Providing insights into how these models respond to degradations caused by irreversible compression, including whether the loss of high-frequency content impacts their ability to accurately identify and diagnose medical conditions.

2. JPEG and JPEG2000 Compression Effects on Medical Images

2.1. Medical Images and Their Characteristics

While natural images are primarily used for visual representation in everyday photography, digital media, and for aesthetic purposes, medical images are critical for diagnostic and therapeutic purposes, requiring higher fidelity and accuracy. Medical images differ significantly from natural images in terms of their formats and uses. Natural images are typically 2D, either in color or grayscale, and usually represented in the RGB color space. In contrast, medical images can come in various formats, including 2D grayscale, 2D with multiple channels, 3D volumetric, and even 4D, which includes an additional temporal dimension representing changes over time [15]. In a single slide 2D grayscale medical image, each pixel (8-, 12-, or 16-bit depth) represents a shade of gray, varying from black to white.

Medical images, unlike natural images, are critical for diagnostic and therapeutic purposes, requiring high fidelity and accuracy. The special characteristics of 2D grayscale medical images, such as their specific variation in intensity ranges, location, scale, and the importance of fine details, make them uniquely challenging for image compression and ML applications. We examine each of these characteristics separately.

2.1.1. Intensity

In general photography or natural images, the exact pixel intensity (i.e., the precise shade of color or brightness) does not usually convey significant information by itself; instead, the overall context and pattern are more important. In contrast, medical imaging relies on specific and exact pixel intensity values to provide critical information, such as the density of the tissue at a given pixel location. The amount of absorption or scatter of electromagnetic waves for a given material is represented by an attenuation coefficient. In CT imaging, specific pixel intensities correspond to Hounsfield Units (HUs), derived from attenuation coefficients representing different types of organic substances [16]. Figure 1 shows the HUs corresponding to specific organic substances. Altering any intensity information may remove crucial diagnostic details relevant for pathology classification or segmentation tasks. It is important to emphasize that medical images such as CT and MRI have sharp edges, i.e., abrupt variations in pixel intensity values, corresponding to boundaries separating various tissue types and ranging from very dark to extremely bright areas. Natural scene images in most cases exhibit more continuous patterns in intensity changes.

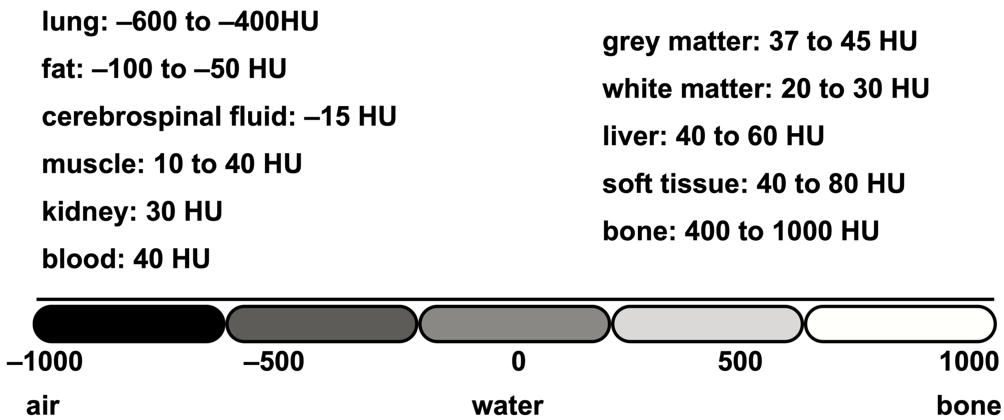

Figure 1. Hounsfield units and corresponding pixel intensity grayscale shades (approximate) associated with tissue type [16].

2.1.2. Location

For natural images, the location of an object is not as crucial as in medical images. In most cases, the object is still the same object in general photography; however, in medical images, certain abnormal tissues are more likely to be present in specific parts of the human body, which can be a crucial piece of information for diagnosis and in ML.

2.1.3. Scale

Scale is another important aspect of medical images. While the scale may provide more detailed information in natural scene images, it is crucial in medical imaging to compute the size of a pathology, for example.

2.2. JPEG and JPEG2000 Compression Techniques

Irreversible image compression techniques are designed to reduce the size of digital images by discarding information deemed less critical for visual perception. A key aspect of this process is the removal of high-frequency components from an image. High-frequency components correspond to rapid changes in intensity, fine and detailed textures, and random noise in an image [17].

The term “JPEG”, originating from the Joint Photographic Experts Group, refers to a lossy compression format standardized in 1993 [18,19]. Known for its effectiveness, JPEG is one of the most widely used compression formats. JPEG compression processes an image by handling each 8 × 8 pixel block independently. Each 8 × 8 pixel block is transformed into the frequency domain with the use of the Discrete Cosine Transform (DCT), converting the original pixels into frequency coefficients. Quality loss is managed using a quality factor ranging from 1 to 100. This factor, along with the corresponding quantization table, scales each frequency coefficient within the 8 × 8 blocks. Quantization tables are designed to preserve the low-frequency coefficients while approximating the high-frequency coefficients, often setting the highest ones to zero for lower quality factors. The quantized coefficients are then rounded and reordered in a zigzag pattern, often resulting in many zeros at higher frequencies. Run-length encoding (RLE) efficiently compresses these zeros, while entropy coding further reduces repetitive values to enhance compression and processing speed. The compressed output file contains the encoded sequence along with the necessary headers for decoding. Decompression reverses these steps to reconstruct the image.

JPEG2000, considered a more efficient compression format compared to JPEG, is a newer algorithm employing multiresolution capabilities based on the Discrete Wavelet Transform (DWT) [20]. A pyramidal structure is formed from sub-band wavelet decomposition, containing image information at several resolutions, including the original image resolution. A significant limitation to consider is that JPEG2000 is not widely supported by most browsers, owing to the complexity associated with its encoding and decoding processes. JPEG, although considered worse in performance than JPEG2000 [21], remains the simplest irreversible compression format for medical images supported in DICOM. The DICOM standard supports grayscale irreversible compression for JPEG2000 for 8-, 12-, and 16-bit images and JPEG for 8- and 12-bit images [8].

2.3. Compression Artifacts and Their Diagnostic Implications

Due to the removal of high-frequency components, irreversible compression methods such as JPEG and JPEG2000 effectively reduce noise while maintaining minimal loss of diagnostic information. By discarding certain image data, these techniques enhance the visual appeal of the decompressed image [17]. However, this reduction in detail can also introduce artifacts, distortions, or anomalies that negatively impact overall image quality. While irreversible compression minimizes the amount of data required for storage or transmission, it results in a loss of finer details and textures, which may affect the accuracy and fidelity of the image. Table 2 provides an overview of the artifacts introduced by JPEG and JPEG2000 compression methods and their implications.

Table 2. JPEG and JPEG2000 compression artifacts and their implications for medical images.

Artifacts	Implications	Compression Algorithms
Blocking Artifacts: Caused by the division of an image into 8 × 8 pixel blocks during compression. Discontinuities can appear at the boundaries of these blocks.	These artifacts can make it difficult to distinguish fine details, such as small lesions or microcalcifications in mammograms [21,22].	JPEG
Ringing Artifacts: Appear as oscillating patterns or halos near sharp transitions or edges in the image, often resulting from high-frequency loss.	Ringing artifacts can interfere with the interpretation of edges and boundaries, which is critical in identifying and measuring abnormalities [23].	JPEG

Table 2. *Cont.*

Artifacts	Implications	Compression Algorithms
Wavelet Artifacts: JPEG2000 uses wavelet transform, which can cause artifacts that appear as ripple-like patterns or smudges, particularly at higher compression rates.	These artifacts can obscure small but clinically significant details, such as small vessels or subtle texture differences [23–25].	JPEG2000
Blurring: Loss of high-frequency detail, leading to a reduction in image sharpness.	Blurring can obscure important diagnostic features, such as the edges of tumors or the fine structures of tissues, potentially leading to misdiagnosis [24–26].	JPEG, JPEG2000

3. DL Model Performance on Compressed Medical Images

DL in Medical Imaging

Deep Neural Networks (DNNs) have substantially advanced medical image processing, enhancing diagnostic accuracy, treatment planning, and patient care. Earlier image analysis techniques relied on manually selected features and expert knowledge, which were often time-intensive and susceptible to human error. Notable milestones include optical scanning for mammogram abnormalities in 1967 [27], automated detection of suspicious lesions in breast radiographs in 1977 [28], and computer-assisted mammogram inspection in 1979 [29]. The emergence of ML aimed to address these challenges by automating feature selection and improving operational efficiency. Traditional ML models, such as Support Vector Machines (SVMs), decision trees, and random forests, require extensive feature engineering to identify relevant inputs [30], and have been applied successfully to tasks like image segmentation, object detection, and disease classification. Techniques such as Fourier, Cosine, Wavelet, and Gabor transforms, along with dimensionality reduction methods like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), were essential for enhancing model performance [31,32]. In contrast, DL models autonomously learn and extract hierarchical features from raw data, thus eliminating the need for manual feature engineering. This capacity has positioned DL as a transformative approach in medical imaging, with applications in Computer-Aided Diagnosis (CAD), lesion detection, organ and tumor segmentation, image enhancement, and patient prognosis [31,33]. Figure 2 illustrates the primary distinctions between ML and DL in diagnostic binary classification tasks.

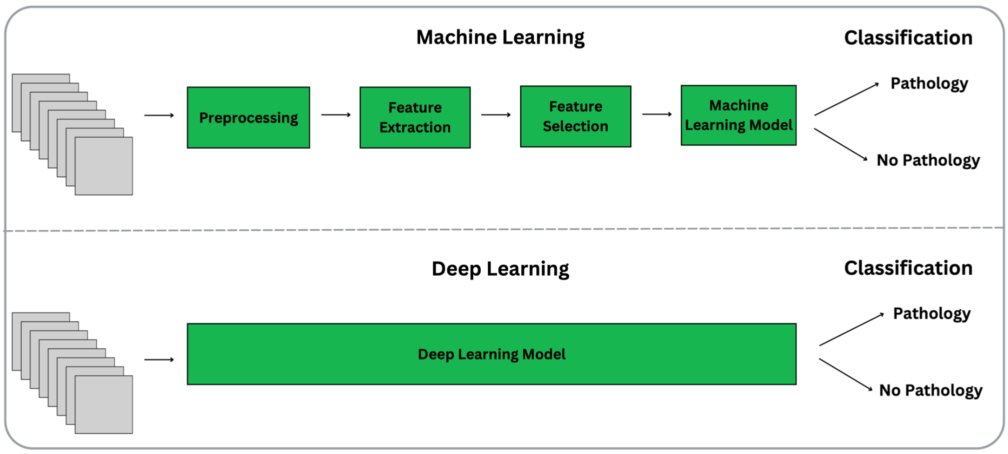

Figure 2. ML versus DL processes for classification problem (high-level).

DL architectures for medical imaging are generally categorized as supervised or unsupervised techniques. In supervised methods, input data include labels, enabling models to learn to predict these labels on unseen data. By contrast, unsupervised techniques identify patterns without the need for labeled data. Convolutional Neural Networks (CNNs) are the most widely employed supervised DL architectures in medical imaging [34]. Known for their strength in image recognition and feature learning, CNNs maintain local spatial relationships within images while also reducing dimensionality efficiently [35].

In medical imaging, classification involves identifying objects or features within an image, such as determining the presence of a specific pathology. Segmentation divides an image into Regions of Interest (RoIs), such as separating tissues or lesion boundaries, while detection identifies and marks specific objects, like liver tumors in CT scans. CNNs are capable of processing both 2D images and 3D volumes like CT or MRI scans [35]. Figure 3 summarizes task types and applications using CNN architectures.

Deep Learning Model	Task	Application
Covolutional Neural Networks (CNNs) (most common)	Image classification	Determining the presence of a specific pathology, such as a tumor
	Image segmentation	Segmenting an image into regions of interest, such as distinguishing various tissues or delineating lesion boundaries.
	Detection	Identifying and localizing specific structures within an image, such as the detection of nodules in lung CT scans.

Figure 3. Types of tasks and applications based on CNNs in medical imaging.

Less common types of supervised DL architectures used in medical imaging are Recurrent Neural Networks (RNNs), which are applied for processing sequences of images or regions, or for generating image captions [35,36]. Generative Adversarial Networks (GANs) are an example of unsupervised learning and are used to generate new data samples (synthesizing realistic medical images) that may be used to train other models [37].

In this work, based on the literature, we analyze how irreversible compression affects classification and segmentation tasks when using CNN architectures for medical images.

Modeled after the architecture of the primary visual cortex [38–41], CNNs are optimized for extracting and learning critical image features [42,43]. Their multi-layered architecture abstracts raw pixel data through layers, including convolutional layers with Rectified Linear Unit (ReLU) activation and pooling layers. Convolutional layers utilize filters to detect localized features (edges, corners, textures), yielding activation maps that reveal the spatial distribution of these features.

ReLU activation functions convert linear input combinations into non-linear outputs, capturing complex relationships and mitigating vanishing gradients, which stabilizes training [44]. Pooling layers reduce spatial dimensions, preserving key information and enhancing feature invariance, which aids in reducing dimensionality and overfitting. Fully connected layers then aggregate localized features into global representations, enabling complex tasks like classification [45]. Figure 4 outlines a basic CNN architecture. In medical imaging, CNN-based architectures like AlexNet [46], VGGNet [47], and ResNet [48] are widely used. However, DL models require large datasets; to address this, transfer learning [49] enables adaptation of pre-trained models on smaller datasets, such as MRI brain tumor segmentation [50]. CNNs are also integral to architectures like U-Net, which employs an encoder–decoder structure for tasks, such as lung CT image segmentation [51,52].

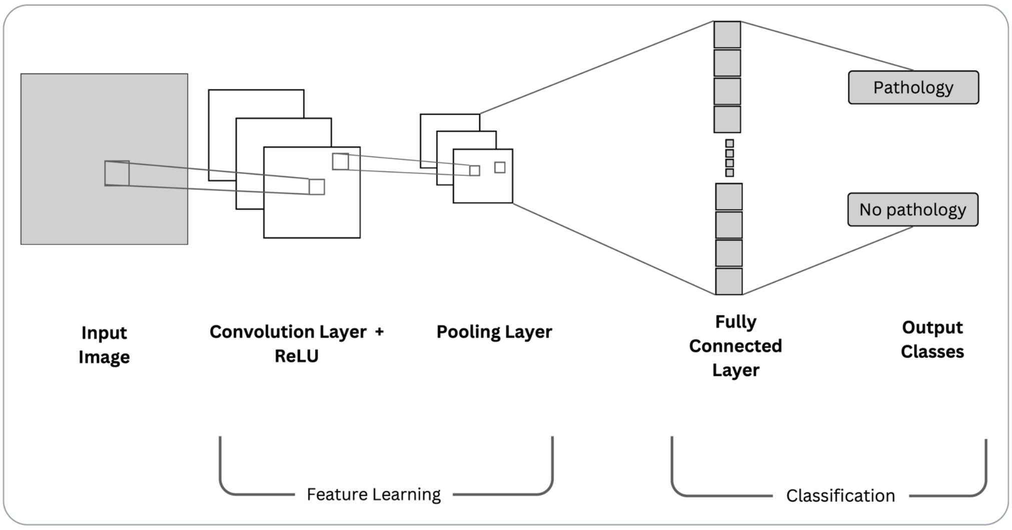

Figure 4. Basic CNN architecture for a binary classification problem.

One of the earliest applications of CNNs was lung nodule detection in chest X-rays [53]. CNNs are expected to optimize routine tasks for medical professionals, potentially enhancing their practice [54]. In some instances, DNN models can surpass radiologists' performance; for example, the study "Radiologists versus Deep Convolutional Neural Networks: A Comparative Study for Diagnosing COVID-19" found that DNNs outperformed radiologists in classifying COVID-19 images, achieving higher accuracy, sensitivity, precision, and F1-score [55]. However, other research indicates that larger datasets are necessary for DNNs to fully match radiologists' performance [56].

This work presents only a high-level overview of selected DL methodologies. However, extensive research has been conducted on the development and modification of complex DL architectures to tackle specific tasks in medical image analysis. A more comprehensive review of DL applications in this field, particularly concerning CNN architectures, can be found in numerous studies [32,34,35,45,54,57–66].

4. DNNs and Irreversibly Compressed Images

DNNs continue to achieve state-of-the-art performance in medical image analysis; however, these models are typically trained and tested on high-quality image datasets. In real-world medical applications, irreversibly compressed images may be the only available input due to factors such as poor internet connections or the irreversible storage formats of historical records. Irreversible compression can present a significant practical challenge that is often overlooked in the design of DNN architectures. Can we assume that DL models trained on uncompressed images will deliver accurate results when applied to irreversibly compressed images? On the other hand, can we train DNN models with compressed medical images to speed up the training time of the models and use the trained models for uncompressed image data? These questions have been the motivation for this work.

We commence this discussion by examining the impact of irreversible compression artifacts on the training and testing of DNN models. For natural images, a study by Dodge et al. [67] showed that the tested DNN models were sensitive to noise and blur distortions but invariant to JPEG and JPEG2000 compression, as well as changes in contrast in a classification task. However, the authors also concluded that training on degraded images may enhance testing results for similar degraded images, but this could potentially result in decreased model performance on uncompressed images. The DNN models demonstrated lower accuracy for images compressed with a JPEG quality factor of less than 10 and a Peak Signal-to-Noise Ratio (PSNR) of less than 30 for JPEG2000. In another study by Dejean-Servières et al. [68], it was shown that the performance of a pre-trained state-of-the-art CNN model improved with higher compression ratios for JPEG. Furthermore, it was concluded that the model relied on artifacts produced by JPEG compression to achieve better classification results. In a study by Pistono et al. [69] with experiments on the MNIST and CIFAR-10 image databases, it was shown that the complexity of DNN learning tasks can be reduced by using partially decompressed images, resulting in minimal accuracy loss. Conversely, the accuracy loss for CNNs depends on the JPEG compression level. A compromise is necessary; for instance, using a quality factor of 80 achieves a 45% reduction in decompression computation complexity at the cost of a 13% accuracy loss. This study also highlights the necessity for models specifically adapted to irreversibly compressed image data. The idea of adapting models to JPEG degraded images has been proposed in the literature by utilizing the use of the DCT frequency coefficients and spectral loss of image information [70]. In 2021, Yong-Yeon et al. [71] published a study examining the impact of JPEG2000 irreversible image compression on DL-based mammogram (CR breast) classification. The authors assert that they are the first to explore how such compression affects DNN models for medical images. Their research involved training CNNs to classify mammograms as malignant or non-malignant using compressed images. The performance of the models began to decline only at extreme compression ratios exceeding 5000:1, where saliency maps failed to accurately reflect the ground truth. Their findings suggest that training and testing models on a single compression ratio do not influence classification performance. Furthermore, the study observed that using a diverse set of images with varying compression ratios improves model generalization when tested across different compression ratios. In Digital Pathology, for example, images can be compressed by 85% while still preserving 95% of the performance of DL algorithms compared to using uncompressed images. Interestingly, the highest level of compression that DL algorithms can handle is often reached when pathologists start to face difficulties in making accurate diagnoses [72]. Table 3 summarizes the results presented above.

Table 3. Summary of literature findings on the impact of irreversible compression artifacts on the training and testing of DNN models in image analysis.

Study	Findings
Dodge et al. (2016) [67]	DNNs were sensitive to noise/blur but robust to JPEG/JPEG2000 compression; training on degraded images improved similar cases but reduced uncompressed accuracy. Performance dropped for quality factor < 10 for JPEG and PSNR < 30 for JPEG2000.
Dejean-Servières et al. (2017) [68]	Higher JPEG compression enhanced CNN classification via compression artifacts.
Chen et al. (2020) [72]	Pathology images retained 95% DL performance at 85% compression; tolerable compression aligned with pathologists' limits.
Pistono et al. (2020) [69]	Partial decompression lowered DNN complexity with minimal accuracy loss; JPEG quality factor of 80 cut computation by 45%, with 13% accuracy reduction.
Yong-Yeon et al. (2021) [71]	Mammogram classification declined only at extreme JPEG2000 compression (>5000:1). Mixed compression ratios improved generalization; single-ratio training/testing preserved accuracy.

Based on the research discussed, training DL models with irreversibly compressed images has emerged as a significant concern in the design of these models for medical image analysis. The literature on the impact of irreversible compression on DL model performance presents varied findings. Some studies indicate that DL models are adversely affected only at extremely high compression ratios, while others suggest improved performance on compressed images due to learning from compression artifacts. Most authors agree that DL models exhibit invariance to irreversibly compressed images at lower compression ratios, while higher ratios do impact training and testing. However, a threshold compression ratio at which models perform better due to learning artifacts has not been established for general modalities or anatomical regions. The existing studies depend on specific datasets, restricting the broader applicability of their conclusions. Consequently, the current evidence is insufficient to form a unified consensus on the effects of irreversible compression on DL models for medical images. These findings provide valuable insights into various methodologies for evaluating DL models with uncompressed, compressed, and mixed image data, establishing a foundation for future studies.

5. Conclusions

In conclusion, the impact of irreversible compression on DL models is complex and not immediately apparent. JPEG and JPEG2000 compression algorithms eliminate high-frequency image information, which may contain details critical for training DL models, even when such distortions are imperceptible to the human eye. However, the high-frequency information discarded during irreversible compression often encompasses noise, which can inadvertently aid models in identifying key image features.

Notably, model performance typically remains largely unaffected by compression until it reaches significantly high levels. In certain instances, the literature indicates that DL models may even perform better when trained with irreversibly compressed images. Conversely, there is a risk that models may learn compression artifacts, which could improve classification accuracy on the training data while complicating generalization to new datasets.

A summary of the advantages and disadvantages of using irreversibly compressed images in DL for medical image analysis is provided as follows:

Advantages:

- May significantly reduce dataset size, leading to shorter model training times.
- Reduces storage costs.
- Allows the utilization of older irreversibly compressed data.

Disadvantages:

- Models may learn compression artifacts during training, reducing their ability to generalize to new images.
- Insufficient published research on the topic.

Overall, the current body of research establishes a strong foundation for addressing this complex issue. Continued investigation is essential to expand our understanding and support the advancement of reliable AI-driven medical technologies.

5.1. General Further Research Suggestions on Using Irreversible Compression for Training DL Models in Medical Image Analysis

Based on the literature review presented, the following list outlines suggested directions for researchers to further explore the use of irreversibly compressed images for training and testing DL models and to assess their accuracy and performance in medical image analysis:

- Train and test models on mixed sets (uncompressed and compressed images) based on the compression ratios recommended for radiology.
- Modify models to handle irreversibly compressed images, such as using DCT frequency coefficients as input to DL models.
- Establish compression thresholds based on model prediction accuracy for more general datasets based on modality and anatomy.
- Create a virtual image dataset featuring basic shapes with subtle variations in shades of gray to represent the range of pixel intensities found in typical medical images for specific modalities and anatomical regions. Use this dataset to evaluate how different compression thresholds impact the accuracy of DNN predictions. This approach of

using shapes and grayscale variations to replicate the structures and edges commonly found in medical images has been proposed in the literature as a method for assessing the quality of scaled medical images [73].

5.2. Conclusive Remarks

This work underscores the critical need for additional research to reach clear and definitive conclusions regarding the impact of irreversible compression on DL models in medical image analysis. While current studies provide valuable insights, the evidence remains inconclusive, particularly concerning the extent to which compression artifacts influence model performance across various imaging modalities and anatomies. Future research should focus on systematically investigating various compression levels, exploring advanced strategies such as creating virtual datasets resembling the shapes and shades of medical images for testing DL models, and establishing recommendations for incorporating irreversibly compressed medical images into DL model training. By addressing these gaps, the scientific community can better understand the nuances of irreversible compression effects on DL, ultimately leading to more robust and reliable AI applications in medical imaging.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. Seeram, E. Irreversible compression in digital radiology. A literature review. *Radiography* **2006**, *12*, 45–59. [CrossRef]
2. Koff, D.A.; Shulman, H. An overview of digital compression of medical images: Can we use lossy image compression in radiology? *J.-Can. Assoc. Radiol.* **2006**, *57*, 211.
3. McInnes, M. *Digital Compression of Medical Images: An Assessment of Legal Risk*; Ivey School, Unversity of Western Ontario: London, ON, Canada, 2005.
4. Flint, A.C. Determining optimal medical image compression: Psychometric and image distortion analysis. *BMC Med. Imaging* **2012**, *12*, 1–7. [CrossRef] [PubMed]
5. Sung, M.M.; Kim, H.J.; Yoo, S.K.; Choi, B.W.; Nam, J.E.; Kim, H.S.; Lee, J.H.; Yoo, H.S. Clinical evaluation of compression ratios using JPEG2000 on computed radiography chest images. *J. Digit. Imaging* **2002**, *15*, 78–83. [CrossRef]
6. European Society of Radiology. Usability of irreversible image compression in radiological imaging. A position paper by the European Society of Radiology (ESR). *Insights Imaging* **2011**, *2*, 103–115. [CrossRef]
7. Koff, D.; Bak, P.; Brownrigg, P.; Hosseinzadeh, D.; Khademi, A.; Kiss, A.; Lepanto, L.; Michalak, T.; Shulman, H.; Volkening, A. Pan-Canadian evaluation of irreversible compression ratios ("lossy" compression) for development of national guidelines. *J. Digit. Imaging* **2009**, *22*, 569–578. [CrossRef]
8. Mustra, M.; Delac, K.; Grgic, M. Overview of the DICOM standard. In Proceedings of the 2008 50th International Symposium ELMAR, Zadar, Croatia, 10–12 September 2008; IEEE: Piscataway, NJ, USA, 2008; Volume 1, pp. 39–44.
9. Suapang, P.; Dejhan, K.; Yimmun, S. Medical image compression and DICOM-format image archive. In Proceedings of the 2009 ICCAS-SICE, Fukuoka, Japan, 18–21 August 2009; IEEE: Piscataway, NJ, USA, 2009; pp. 1945–1949.
10. Koff, D.; Bak, P.; Matos, A.; Norman, G. Evaluation of irreversible compression ratios for medical images thin slice CT and update of Canadian Association of Radiologists (CAR) guidelines. *J. Digit. Imaging* **2013**, *26*, 440–446. [CrossRef]
11. The Royal Australian and New Zealand College of Radiologists. *Guideline for the Use of Image Compression in Diagnostic Imaging, Version 2*; Technical Report; The Royal Australian and New Zealand College of Radiologists: Sydney, Australia, 2020.
12. Norweck, J.T.; Seibert, J.A.; Andriole, K.P.; Clunie, D.A.; Curran, B.H.; Flynn, M.J.; Krupinski, E.; Lieto, R.P.; Peck, D.J.; Mian, T.A.; et al. AACR–AAPM–SIIM Technical Standard for Electronic Practice of Medical Imaging. *J. Digit. Imaging* **2013**, *26*, 38–52. [CrossRef]
13. Radiologists, R. *The Adoption of Lossy Image Data Compression for the Purpose of Clinical Interpretation*; Royal College of Radiologists: London, UK, 2008.
14. Loose, R.; Braunschweig, R.; Kotter, E.; Mildenberger, P.; Simmler, R.; Wucherer, M. Compression of digital images in radiology-results of a consensus conference. *RoFo Fortschritte Geb. Rontgenstrahlen Nukl.* **2008**, *181*, 32–37. [CrossRef]

15. Sriramakrishnan, P.; Kalaiselvi, T.; Padmapriya, S.; Shanthi, N.; Ramkumar, S.; Kalaichelvi, N. An medical image file formats and digital image conversion. *Int. J. Eng. Adv. Technol.* **2019**, *9*, 74–78. [CrossRef]
16. Feeman, T.G. *The Mathematics of Medical Imaging*; Springer: Berlin/Heidelberg, Germany, 2010.
17. Persons, K.; Palisson, P.; Manduca, A.; Erickson, B.J.; Savcenko, V. An analytical look at the effects of compression on medical images. *J. Digit. Imaging* **1997**, *10*, 60–66. [CrossRef] [PubMed]
18. Wallace, G.K. The JPEG still picture compression standard. *Commun. ACM* **1991**, *34*, 30–44. [CrossRef]
19. Wallace, G.K. The JPEG still picture compression standard. *IEEE Trans. Consum. Electron.* **1992**, *38*, 28–34. [CrossRef]
20. Skodras, A.; Christopoulos, C.; Ebrahimi, T. The JPEG 2000 still image compression standard. *IEEE Signal Process. Mag.* **2001**, *18*, 36–58. [CrossRef]
21. Shiao, Y.H.; Chen, T.J.; Chuang, K.S.; Lin, C.H.; Chuang, C.C. Quality of compressed medical images. *J. Digit. Imaging* **2007**, *20*, 149–159. [CrossRef]
22. Good, W.F.; Sumkin, J.H.; Ganott, M.; Hardesty, L.; Holbert, B.; Johns, C.M.; Klym, A.H. Detection of masses and clustered microcalcifications on data compressed mammograms: An observer performance study. *Am. J. Roentgenol.* **2000**, *175*, 1573–1576. [CrossRef]
23. Fidler, A.; Skaleric, U.; Likar, B. The impact of image information on compressibility and degradation in medical image compression. *Med. Phys.* **2006**, *33*, 2832–2838. [CrossRef]
24. Erickson, B.J. Irreversible compression of medical images. *J. Digit. Imaging* **2002**, *15*, 5–14. [CrossRef]
25. Woo, H.S.; Kim, K.J.; Kim, T.J.; Hahn, S.; Kim, B.; Kim, Y.H.; Lee, K.H. JPEG 2000 compression of abdominal CT: Difference in tolerance between thin-and thick-section images. *Am. J. Roentgenol.* **2007**, *189*, 535–541. [CrossRef]
26. Kalyanpur, A.; Neklesa, V.P.; Taylor, C.R.; Daftary, A.R.; Brink, J.A. Evaluation of JPEG and wavelet compression of body CT images for direct digital teleradiologic transmission. *Radiology* **2000**, *217*, 772–779. [CrossRef]
27. Winsberg, F.; Elkin, M.; Macy, J., Jr.; Bordaz, V.; Weymouth, W. Detection of radiographic abnormalities in mammograms by means of optical scanning and computer analysis. *Radiology* **1967**, *89*, 211–215. [CrossRef]
28. Kimme, C.; O'loughlin, B.J.; Sklansky, J. Automatic detection of suspicious abnormalities in breast radiographs. In *Data Structures, Computer Graphics, and Pattern Recognition*; Elsevier: Amsterdam, The Netherlands, 1977; pp. 427–447.
29. Spiesberger, W. Mammogram inspection by computer. *IEEE Trans. Biomed. Eng.* **1979**, *26*, 213–219. [CrossRef] [PubMed]
30. Barragán-Montero, A.; Javaid, U.; Valdés, G.; Nguyen, D.; Desbordes, P.; Macq, B.; Willems, S.; Vandewinckele, L.; Holmström, M.; Löfman, F.; et al. Artificial intelligence and machine learning for medical imaging: A technology review. *Phys. Medica* **2021**, *83*, 242–256. [CrossRef] [PubMed]
31. Panayides, A.S.; Amini, A.; Filipovic, N.D.; Sharma, A.; Tsaftaris, S.A.; Young, A.; Foran, D.; Do, N.; Golemati, S.; Kurc, T.; et al. AI in Medical Imaging Informatics: Current Challenges and Future Directions. *IEEE J. Biomed. Health Inform.* **2020**, *24*, 1837–1857. [CrossRef] [PubMed]
32. Rana, M.; Bhushan, M. Machine learning and deep learning approach for medical image analysis: Diagnosis to detection. *Multimed. Tools Appl.* **2023**, *82*, 26731–26769. [CrossRef]
33. Kim, M.; Yun, J.; Cho, Y.; Shin, K.; Jang, R.; Bae, H.j.; Kim, N. Deep learning in medical imaging. *Neurospine* **2019**, *16*, 657. [CrossRef]
34. Litjens, G.; Kooi, T.; Bejnordi, B.E.; Setio, A.A.A.; Ciompi, F.; Ghafoorian, M.; Van Der Laak, J.A.; Van Ginneken, B.; Sánchez, C.I. A survey on deep learning in medical image analysis. *Med. Image Anal.* **2017**, *42*, 60–88. [CrossRef]
35. Ker, J.; Wang, L.; Rao, J.; Lim, T. Deep learning applications in medical image analysis. *IEEE Access* **2017**, *6*, 9375–9389. [CrossRef]
36. Zhang, H.; Qie, Y. Applying deep learning to medical imaging: A review. *Appl. Sci.* **2023**, *13*, 10521. [CrossRef]
37. Radford, A.; Metz, L.; Chintala, S. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv* **2015**, arXiv:1511.06434.
38. Riesenhuber, M.; Poggio, T. Computational Models of Object Recognition in Cortex: A Review. 2000. Available online: http://hdl.handle.net/1721.1/7231 (accessed on 24 August 2024).
39. Hubel, D.H.; Wiesel, T.N. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. *J. Physiol.* **1962**, *160*, 106. [CrossRef] [PubMed]
40. Fukushima, K. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. *Biol. Cybern.* **1980**, *36*, 193–202. [CrossRef] [PubMed]
41. Celeghin, A.; Borriero, A.; Orsenigo, D.; Diano, M.; Méndez Guerrero, C.A.; Perotti, A.; Petri, G.; Tamietto, M. Convolutional neural networks for vision neuroscience: Significance, developments, and outstanding issues. *Front. Comput. Neurosci.* **2023**, *17*, 1153572. [CrossRef] [PubMed]
42. Yamashita, R.; Nishio, M.; Do, R.K.G.; Togashi, K. Convolutional neural networks: An overview and application in radiology. *Insights Imaging* **2018**, *9*, 611–629. [CrossRef]
43. Mall, P.K.; Singh, P.K.; Srivastav, S.; Narayan, V.; Paprzycki, M.; Jaworska, T.; Ganzha, M. A comprehensive review of deep neural networks for medical image processing: Recent developments and future opportunities. *Healthc. Anal.* **2023**, *4*, 100216. [CrossRef]
44. Glorot, X.; Bordes, A.; Bengio, Y. Deep sparse rectifier neural networks. In Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, JMLR Workshop and Conference Proceedings, Fort Lauderdale, FL, USA, 1–13 April 2011; pp. 315–323.

45. Alzubaidi, L.; Zhang, J.; Humaidi, A.J.; Al-Dujaili, A.; Duan, Y.; Al-Shamma, O.; Santamaría, J.; Fadhel, M.A.; Al-Amidie, M.; Farhan, L. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *J. Big Data* **2021**, *8*, 1–74. [CrossRef]
46. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. ImageNet classification with deep convolutional neural networks. *Commun. ACM* **2017**, *60*, 84–90. [CrossRef]
47. Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. *arXiv* **2014**, arXiv:1409.1556.
48. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.
49. Tajbakhsh, N.; Shin, J.Y.; Gurudu, S.R.; Hurst, R.T.; Kendall, C.B.; Gotway, M.B.; Liang, J. Convolutional neural networks for medical image analysis: Full training or fine tuning? *IEEE Trans. Med. Imaging* **2016**, *35*, 1299–1312. [CrossRef]
50. Ghafoorian, M.; Mehrtash, A.; Kapur, T.; Karssemeijer, N.; Marchiori, E.; Pesteie, M.; Guttmann, C.R.; de Leeuw, F.E.; Tempany, C.M.; Van Ginneken, B.; et al. Transfer learning for domain adaptation in mri: Application in brain lesion segmentation. In Proceedings of the Medical Image Computing and Computer Assisted Intervention-MICCAI 2017: 20th International Conference, Proceedings, Part III 20, Quebec City, QC, Canada, 11–13 September 2017; Springer: Berlin/Heidelberg, Germany, 2017; pp. 516–524.
51. Ronneberger, O.; Fischer, P.; Brox, T. U-net: Convolutional networks for biomedical image segmentation. In Proceedings of the Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015: 18th International Conference, Proceedings, Part III 18, Munich, Germany, 5–9 October 2015; Springer: Berlin/Heidelberg, Germany, 2015; pp. 234–241.
52. Skourt, B.A.; El Hassani, A.; Majda, A. Lung CT image segmentation using deep neural networks. *Procedia Comput. Sci.* **2018**, *127*, 109–113. [CrossRef]
53. Lo, S.C.; Lou, S.L.; Lin, J.S.; Freedman, M.; Chien, M.; Mun, S. Artificial convolution neural network techniques and applications for lung nodule detection. *IEEE Trans. Med. Imaging* **1995**, *14*, 711–718. [CrossRef] [PubMed]
54. Fourcade, A.; Khonsari, R.H. Deep learning in medical image analysis: A third eye for doctors. *J. Stomatol. Oral Maxillofac. Surg.* **2019**, *120*, 279–288. [CrossRef] [PubMed]
55. Helwan, A.; Ma'aitah, M.K.S.; Hamdan, H.; Ozsahin, D.U.; Tuncyurek, O. Radiologists versus Deep Convolutional Neural Networks: A Comparative Study for Diagnosing COVID-19. *Comput. Math. Methods Med.* **2021**, *2021*, 5527271. [CrossRef] [PubMed]
56. Roest, C.; Fransen, S.J.; Kwee, T.C.; Yakar, D. Comparative performance of deep learning and radiologists for the diagnosis and localization of clinically significant prostate cancer at MRI: A systematic review. *Life* **2022**, *12*, 1490. [CrossRef] [PubMed]
57. Shen, D.; Wu, G.; Suk, H.I. Deep learning in medical image analysis. *Annu. Rev. Biomed. Eng.* **2017**, *19*, 221–248. [CrossRef]
58. Razzak, M.I.; Naz, S.; Zaib, A. Deep learning for medical image processing: Overview, challenges and the future. In *Classification in BioApps: Automation of Decision Making*; Springer: Cham, Switzerland, 2018; pp. 323–350.
59. Chen, X.; Wang, X.; Zhang, K.; Fung, K.M.; Thai, T.C.; Moore, K.; Mannel, R.S.; Liu, H.; Zheng, B.; Qiu, Y. Recent advances and clinical applications of deep learning in medical image analysis. *Med. Image Anal.* **2022**, *79*, 102444. [CrossRef]
60. Suganyadevi, S.; Seethalakshmi, V.; Balasamy, K. A review on deep learning in medical image analysis. *Int. J. Multimed. Inf. Retr.* **2022**, *11*, 19–38. [CrossRef]
61. Zhou, S.K.; Greenspan, H.; Shen, D. *Deep Learning for Medical Image Analysis*; Academic Press: Cambridge, MA, USA, 2023.
62. Carin, L.; Pencina, M.J. On deep learning for medical image analysis. *JAMA* **2018**, *320*, 1192–1193. [CrossRef]
63. Lu, L.; Zheng, Y.; Carneiro, G.; Yang, L. *Deep Learning and Convolutional Neural Networks for Medical Image Computing*; Advances in Computer Vision and Pattern Recognition; Springer: Cham, Switzerland, 2017.
64. Raza, K.; Singh, N.K. A tour of unsupervised deep learning for medical image analysis. *Curr. Med. Imaging* **2021**, *17*, 1059–1077.
65. Zhang, Y.; Gorriz, J.M.; Dong, Z. Deep learning in medical image analysis. *J. Imaging* **2021**, *7*, 74. [CrossRef] [PubMed]
66. Mishra, S.; Tripathy, H.K.; Acharya, B. A precise analysis of deep learning for medical image processing. In *Bio-Inspired Neurocomputing*; Springer: Singapore, 2021; pp. 25–41.
67. Dodge, S.; Karam, L. Understanding how image quality affects deep neural networks. In Proceedings of the 2016 Eighth International Conference on Quality of Multimedia Experience (QoMEX), Lisbon, Portugal, 6–8 June 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6.
68. Dejean-Servières, M.; Desnos, K.; Abdelouahab, K.; Hamidouche, W.; Morin, L.; Pelcat, M. Study of the Impact of Standard Image Compression Techniques on Performance of Image Classification with a Convolutional Neural Network. Ph.D. Thesis, INSA Rennes: Rennes, France; University Rennes: Rennes, France; IETR: Rennes, France; Institut Pascal: Aubière, France, 2017.
69. Pistono, M.; Coatrieux, G.; Nunes, J.C.; Cozic, M. Training Machine Learning on JPEG Compressed Images. In Proceedings of the DCC, Snowbird, UT, USA, 24–27 March 2020; p. 388.
70. Gueguen, L.; Sergeev, A.; Kadlec, B.; Liu, R.; Yosinski, J. Faster neural networks straight from jpeg. In Proceedings of the Advances in Neural Information Processing Systems, Montreal, QC, Canada, 2–8 December 2018; Volume 31.
71. Jo, Y.Y.; Choi, Y.S.; Park, H.W.; Lee, J.H.; Jung, H.; Kim, H.E.; Ko, K.; Lee, C.W.; Cha, H.S.; Hwangbo, Y. Impact of image compression on deep learning-based mammogram classification. *Sci. Rep.* **2021**, *11*, 7924. [CrossRef] [PubMed]

72. Chen, Y.; Janowczyk, A.; Madabhushi, A. Quantitative assessment of the effects of compression on deep learning in digital pathology image analysis. *JCO Clin. Cancer Inform.* **2020**, *4*, 221–233. [CrossRef] [PubMed]
73. Urbaniak, I.; Wolter, M. Quality assessment of compressed and resized medical images based on pattern recognition using a convolutional neural network. *Commun. Nonlinear Sci. Numer. Simul.* **2021**, *95*, 105582. [CrossRef]