Image Compression on Digital Pathology: A Review

Abstract

Digital pathology, which refers to the digitalization of tissue slides, is a transformative technology that is beginning to be used in clinical diagnostic processes and computational pathology research. Digitization process yields large sizes of digital slides that include huge amounts of bits which becomes a primary problem for transferring, analyzing, and storing these files. As a result, image compression has become a crucial technique for reducing the size of digital slides, transferring a file from point a to point b faster, and decreasing storage cost in digital pathology. This review article includes traditional image compression methods as well as deep learning approaches to achieve improved image compression with high accuracy, reduce loss, and improve image visibility.

1. Introduction

Nowadays, Medical imaging forms a key part of clinical diagnosis, and improvements in the quality and type of information available from such images have extended the diagnostic accuracy and range of new applications in health care [24]. Medical imaging facilities are incorporating different image modalities such as Computed Tomography (CT), Magnetic resonance Imaging (MRI), Positron Emission tomography (PET), Digital Subtraction Angiography (DSA) and Digital Pathology (DP). Actually, the use of digital imaging modalities in radiology has grown rapidly over the last decade, with around 15% of the radiographs collected in a hospital being produced directly in digital form [11].

Imaging modalities are the processes by which digital images of various regions of the human body are created, allowing physicians to investigate and identify diseases in patients [22]. As a result, displaying images digitally improves image transmission and organization while also allowing visual diagnostic information to be handled in innovative and useful ways. As the technology advances, diagnostic multi-modality imaging data increases immensely. Therefore, archiving and transmitting digital images becomes one of the potential problems. There are a large number of studies investigating image compression techniques for medical images. In this review, we will focus only on compression methods applied to digital pathology images, which are much larger in size compared to other medical imaging modalities.

Pathology is the study and analysis of illness via the examination of body tissue, which is often fixed on glass slides and examined under a magnifying tool (i.e. microscopes). In today's practice, pathologists perform the majority of clinical studies on glass slides in order to make a diagnosis. While waiting for the glass slide or material to be physically transported to the proper pathologist, initial diagnoses and subsequent second opinions are frequently delayed, and patient treatment may be halted. As a result of the increased use of digital imaging in pathology, particularly the development and implementation of whole slide imaging technologies, Diagnostic Pathology is entering an exciting period. Despite extensive study and technical progress, critical technological issues regarding the actual clinical use of whole-slide imaging (WSI) in pathology remain unresolved. The size of the digitized slide is one of the primary dares. The given slides are really rather large, which affects the transmission speeds at which they are acquired for display from a server or storage device, as well as the amount of storage space they occupy. Therefore, storing, transmitting, and receiving digital data without multiple compression would be costly.

Image compression is the process of encoding information in fewer bits than a compressed representation using specific encoding schemes (Lossy and Lossless). Its primary objective is to reduce the amount of image data while preserving the visual image details [22]. Lossless compression methods are reversible, and the rebuilt image after compression is numerically equal to the original image, with no information loss. These methods, such as PNG [2], often have poor compression ratios. However, with lossy compression algorithms such as JPEG [19], JPEG2000 [13] the compressed data is a near approximation rather than the same as the original data. Lossy compression methods are not fully invertible and often have a greater compression ratio than lossless ones. Common lossy compression algorithms can be divided into traditional approaches based on quantitative statistics and neural network methods based on deep learning. Most conventional approaches are characterized by statistics of the data and use various mathematical al-

gorithms to compress images. Meanwhile, Deep learning-based methods mostly use artificial neural networks to design image codecs. These approaches, which make use of the neural network's great learning capacity, can analyze image features through backpropagation and realize image information reduction without requiring too much prior knowledge [20].
Therefore, this article explores conventional image compression algorithms and intelligent methods based on deep learning. This article is organized as follows. Section 2 presents deep learning techniques (such as Convolutional Neural Network and Recurrent Neural Network) that are used in the medical imaging field. Section 3 reviews the prior Image Compression studies in Digital Pathology using Standard Compressors and Deep Learning Techniques. Section 4 provides previous methods used along with their results. Section 5 covers most popular public histopathology datasets. The discussion on summarizing findings from previous studies will be present in Section 6. Finally, section 7 is devoted to concluding our research.

2. Deep Learning

Deep Learning (DL), also known as deep neural networks or neural learning, is a kind of Artificial Intelligence (AI) that attempts to mimic the operations of the human brain. DL and AI are interchangeably being used through the literature. DL is also a subclass of Machine Learning (ML) to extract features with its self-learning ability. DL includes multiple sequential layers that work throughout a nonlinear decision-making process, and it excels at tasks like visual perception, speech recognition, and language translation. DL models, such as convolutional neural networks (CNN), have gained popularity in computer vision for image classification [9] and have been widely used in medical imaging. DL has been used in digital pathology for the purpose of object detection, segmentation, and tissue classification. These automated algorithms are very relevant for nuclei detection, mitosis quantification, and tubule counting [18].

3. Methods and Results

Despite extensive study and technical progress, critical technological issues regarding the actual clinical use of whole-slide imaging (WSI) in pathology remain unresolved where the size of the digitized slide is one of the primary difficulties. The given slides are really rather large, which affects the transmission speeds at which they are acquired for display from a server or storage device, as well as the amount of storage space they require. This difficulty is further exacerbated by the clinical job, since some instances require just a low-resolution scan, but others demand greater resolutions. Therefore, image compression techniques have appeared to deal with this large quantity of data, but it is difficult to pinpoint a single appropriate compression threshold for all clinical scenarios. For that reason, few thorough investigations of the impact of image compression on diagnostic performance with WSI slides have been conducted.
Nowadays, automated techniques to medical image analysis have been quickly evolving with the goal of delivering clinical information, incorporating second views, and minimizing human interaction. Methods based on deep learning are exponentially developing in the medical imaging field as they have outperformed state-of-the-art methods in virtually all medical imaging areas. Lately, neural networks, especially CNNs, have recently achieved considerable progress in many areas, such as image comprehension, processing, and compression. These techniques become more and more handy especially in Digital Pathology. Image analysis algorithms enable pathologists to create decision support algorithms by performing higher-level, supervised learning tasks such as disease grading.

3.1. Conventional Method on Digital Pathology

In this section, we summarize previous works using conventional compression methods for digital pathology.
Zanjani et al. [23] investigated the impact of JPEG 2000 compression on their proposed CNN-based algorithm, to detect tumor metastases in hematoxylin and eosin-stained tissue sections of breast lymph nodes. It has produced performance comparable to that of pathologists and which was ranked second place in the CAMELYON17 challenge. Their method was evaluated and compared with the pathologists' diagnoses in three different experimental setups: High-quality training data and evaluation on lower-quality images, training and testing on Images of the same quality, evaluation on varying-quality images with fixed compressed trained images. This method was done by extracting 150k positive samples and 500k negative samples, compressed by the JPEG 2000 algorithm using 14 different compression ratios (1:1, 2:1, 4:1, 8:1, 12:1, 16:1, 24:1, 32:1, 48:1, 64:1, 96:1, 128:1, 164:1, 256:1) Its impact is evaluated in three distinct scenarios :

- Train CAD system on high-quality uncompressed images and evaluate on compressed low-quality images with several compression ratios.
- Train CAD system and test on the same level of compression (e.g. train model on compressed images by factor of 32 and evaluated by the same factor).
- Train CAD system on images compressed with the maximal compression ratio that still allowed the classification performance to be above a predefined threshold (e.g., ¡10% drop from the maximum F1 score) and it is evaluated with test images with both lower and higher compression ratio.

In scenario 1, it can be observed that up to a factor of 24, the performance does not show considerable changes, but for a ratio of 32:1, the F1 score drops to 0.908. As the F1 scores and the PR curves illustrate, a factor of 24 shows a trade-off between performance and compression. Scenario 2 shows that the difference between the performance of the model under different compression ratios is minimal.In comparison with the performance of the model in the previous experiment (scenario 1), the improvement is significant per compression rate. The F1 score for compressed images with the factor of 164 is equal to 0.934, whereas when the model is trained on high-quality images, its F1 score is only 0.586. This represents about 59While in scenario 3, in comparison with the second experiment, the performance slightly decreases on either side of the trained compression ratio. The trained CNN model on the low-quality images, (e.g., with compression ratio of 48:1) can perform almost equally well on all higher-quality images and even on the slightly lower-quality samples.

Similarly, Chen et al. [5] studied the effects of image compression on the performance of Deep Learning strategies in 3 use cases: Segmentation of nuclei (n = 137), segmentation of lymph node metastasis (n = 380), lymphocyte detection (n = 100), where each use case were evaluated by a DL classifier at various levels of compression using JPEG (Quality Factor ranging from 1-100) and JPEG2000 (Peak Signal-to-noise ratio ranging from 18-100 dB). Each use case, an AlexNet16 was trained using high-fidelity regions of interest (ROIs) cropped from whole slide images (WSIs) generated by Aperio scanners (Leica Biosystems, Nussloch, Germany) using default settings. During training, some data augmentation settings were applied (e.g. random rotations, random mirroring). Subsequently, held-out test images were subjected to increasing levels of compression, and the relationship between compression level and a number of quantitative performance metrics (e.g., pixel-level F1 score, object detection F1 score, and pixel-level area under the receiver operating characteristic curve[AUC]) was studied. For Case 1, Pathologists identified a PSNR of 30 dB as the maximum compression level they would feel comfortable performing the same segmentation task. This corresponds to a compression ratio of 3% and is close to the point at which performance of the DL classifier starts to degrade dramatically. Meanwhile for case 2, Pathologists reported a PSNR of 22 dB (corresponds to a compression ratio of 1%) as the maximal compression level that would allow them to confidently segment the regions of lymph node metastasis. Any PSNR lower than this value induced too much uncertainty in identifying the cancer boundary. This PSNR level is lower than that for acceptable DL performance (pixel-level AUC of 0.79 at 4% compression ratio) but still within a comparable range. Finally for case 3, The pathologists reported a PSNR of 30 dB (corresponds to a compression ratio of 7%) as the maximum compression level that would allow them to confidently differentiate lymphocytes from other types of cells. Any PSNR lower than this value could cause false identification, likely as a result of color and edge distortions. This PSNR level is higher than that for acceptable DL performance (detection F score of 0.89 at 5% compression ratio) but still within a comparable range.

Thus, Krupinski et al. [10] aimed to determine to what degree whole-slide images (WSI) can be compressed without impacting the ability of the pathologist to distinguish benign from malignant tissues by the extraction of 100 regions of interest (ROIs) from a breast biopsy whole-slide images at five levels of JPEG 2000 compression (8:1, 16:1, 32:1, 64:1, and 128:1) plus the uncompressed version were shown to six pathologists to determine benign versus malignant status. The 100 regions of interest (512 × 512 pixels) were initially zoomed to the same level of magnification and cropped by an experienced pathologist (not participating in the ROC study) from a set of breast biopsy WSI slides (acquired with the DMetrix scanner; DMetrix, Inc., Tucson, AZ, USA) (half benign, half malignant), then compressed using the Kakadu 6.0 implementation of JPEG 2000 to 6 levels (original uncompressed, 8:1, 16:1, 32:1, 64:1, and 128:1) and randomized to create a set of 600 test images. Six pathologists (three Board Certified pathologists; two Fellows; one senior level (PGY4) pathology resident) viewed each set of images on a Barco Coronis Fusion 6MP (Barco NV, Belgium) color display (maximum luminance 400 cd/m2) to determine whether each image was benign or malignant and report their confidence in that decision using a 6-point scale(without having access to the original glass slides). The results were analyzed using the Multi-Reader MultiCase (MRMC) ROC technique. Their experimental results show a significant decrease in performance as a function of compression ratio (F = 14.58, P ¡ 0.0001). The visibility of compression artifacts in the test images was predicted using a visual discrimination model (VDM). Just-noticeable difference (JND) metrics were computed for each image, including the mean, median, 90th percentiles, and maximum values and for comparison PSNR (peak signal-to-noise ratio) and Structural Similarity (SSIM). Image distortion metrics were computed as a function of compression ratio and averaged across test images. All of the JND metrics were found to be highly correlated and differed primarily in magnitude. Both PSNR and SSIM decreased with bit rate, correctly reflecting a loss of image fidelity with increasing compression. Observer performance as measured by the Receiver Operating Characteristic area under the curve (ROC Az) was nearly constant up to a compression ratio of 32:1, then decreased significantly for 64:1 and 128:1 compression levels. The initial decline in Az occurred around a mean JND of 3, Minkowski JND of 4, and 99th percentile JND of 6.5.

In addition, Helin et aI. [8] defined an optimized parametrization for JPEG 2000 image compression to be used specifically with histopathological WSIs. This parametrization is based on allowing a very high degree of compression on the background part of the WSI while using a conventional amount of compression of the tissue-containing part of the image. This method defines JP2-WSI compression to match the image quality of hematoxylin and eosin stained tissue sections scanned and stored with JPEG level 80 compression, followed by maximal compression of the empty slide area (the background). Peak signal-to-noise ratio (PSNR) measurements and visual inspection by two senior pathologists (TT and JI) were used to assess the image quality of the tissue. Comparing the compression power of JP2-WSI to the commonly used fixed 35:1 compression ratio JPEG 2000 and the default image formats of proprietary Aperio, Hamamatsu, and 3DHISTECH scanners, JP2-WSI produced the smallest file sizes and highest overall compression ratios for all 17 slides tested. The image quality, as judged by visual inspection and peak signal-to-noise ratio (PSNR) measurements, was equal to or better than the compared image formats. The average file size by JP2-WSI amounted to 15, 9, and 16 percent respectively, of the file sizes of the three commercial scanner vendors' proprietary file formats (3DHISTECH MRXS, Aperio SVS, and Hamamatsu NDPI).

Meanwhile Sharma et aI. [14] focused more on finding the balance between quality and performance for daily high volume whole slide imaging by scanning two sets of 8 special stains slides each at 0.50 μm/pixel resolution in Hamamatsu scanner at six and five Quality Factor levels using JPEG Compressor respectively to generate 72 images which were observed at a calibrated monitor by imaging specialists, a histo-technician, and a pathologist to find the most suitable Quality Factor level for special stains in digital slides. This method was accomplished by selecting 16 slides in 12 stains: Trichrome, Periodic Acid Schiff, Reticulin, Gomori methenamine silver, Giemsa, Brown-Hopps-Gram, Steiner, WarthinStarry, Mucicarmine, Elastic, Periodic Acid SchiffDiastase, and Congo-Red. The slides were scanned by a Whole slide scanner Nanozoomer 2.0 HT. These slides were scanned with 0.50m/pixel resolution. The first set (human tissue) was scanned at five QF levels: 30, 50, 70, 80 and 90 while the second set (mouse embryo) was scanned at 30, 50, 80 and 90. This experiment used 72 images, 40 for the first set and 32 for the second set. The images were analyzed with a calibrated monitor MDCC 6130 DL (Barco, Kortrij, Belgium) by four people: two imaging specialists, a histo-technician, and a pathologist for various quality factors with an objective to find the most suitable QF level for special stains in digital slides. Their experimental results show that 0.50 μm/pixel images at QF 50 or above were found to be suitable for high volume special stained WSI. The average reduction in storage space by moving from QF 90 to QF 50 is 62.73%. These experiments can be advanced further by applying a quantitative benchmarking tool for judging the image quality to avoid the limitations and variations of human observation.

Table 1 summarizes the methodology and results of each conventional image compression approach.

3.2. Deep Learning Compressors on Digital Pathology

In this section, we summarize previous works using image compression based on deep learning for digital pathology. Image compression is a hidden aspect for most relevant works. However, to the best of our knowledge, a thorough comparison of state of the art solutions for image compressions in the medical domain is still missing. This issue was due to the fact that deep learning models will not evaluate the input data against other sources that are outside the scope of the original model. Therefore, many researchers were relying on their own designed AutoEncoders.

Tuluptceva et al. [16] proposed a new method that uses an autoencoder to understand the representation of the normal data, with optimization being performed with regard to perceptual loss in the regime of progressive growing training. They provide a loss function that measures "content dissimilarity" of the input and the output (the dissimilarity between the overall spatial structures present in the two images, without comparing the exact pixel values), which is called Deep Perceptual Autoencoder. This method uses nothing but the perceptual loss to train the autoencoder and to compute the restoration error during the evaluation. Their proposed method achieves 93.4 ROC AUC1 in the detection of metastases in H&E stained images of lymph nodes on Camelyon16 dataset, and 92.6 in the detection of abnormal chest X-rays on the subset of NIH dataset, which outperforms SOTA methods (by 2.8% and 5.2% in absolute value, respectively).

Next, Wu et al. [21] propose a novel two-stage survival prediction model named ICSPM to join the IHC images and clinicopathological features:

- In stage 1, SDAE-GAN compresses high dimensional IHC images to represent them as 1-dimensional feature vectors and perform data augmentation by a novel policy gradient based method.
- In stage 2, a DenseNet uses these compact and representative feature vectors together with patients' clinicopathological features to predict their five-year survival

The SDAE-GAN leverages the strengths of two unsupervised learning methods, the auto-encoder and the GAN architecture, to recognize salient patterns of these images better. It uses a stacked auto-encoder as the generator of the

GAN and uses dense convolution blocks and deconvolution layers to constitute the auto-encoder. The GAN architecture is involved to train the stacked auto-encoder to output more realistic images (the higher quality of output images leads to the more accurate feature representation of original IHC images). Their experimental results indicate that IC-SPM outperforms existing models on cancer liver survival prediction using only clinicopathological features. It got an AUC score at 0.73 and an accuracy of 0.72. For sensitivity and specificity, it earned 0.75 and 0.66 respectively.
In another study, Roy et al. [12] propose an automated deep learning-based model, named HistoCAE, for segmentation of viable tumors in liver WSIs. A multi-resolution CAE based framework was established for image reconstruction, followed by a classification module that labels each image patch as either tumor or non-tumor using a customized reconstruction loss function for better image reconstruction and tumor segmentation. The CAE is one type of autoencoder specifically designed to learn the compact representation of a given image data manifold. The encoded feature map ($16 \times 16 \times 64$ in size) generated from hE of hCAE module to represent the corresponding high-resolution image of $256 \times 256 \times 3$ in size. Their experimental results indicate that their proposed model presents superior performance than other benchmark models, suggesting its efficacy for viable tumor segmentation using liver WSIs.
Finally, Tellez et al. [15] presents a convolutional neural networks method for gigapixel image analysis on weak image-level labels by:

- Proposing a Neural Image Compression (NIC) as a method to reduce gigapixel images to highly compact representations, suitable for training a CNN end-to-end to predict image-level labels using standard deep learning techniques.
- Comparing several encoding methods that map high-resolution image patches to low-dimensional embedding vectors based on different unsupervised learning techniques: reconstruction error minimization, contrastive training, and adversarial feature learning.
- Evaluating NIC in three publicly available datasets: a synthetic set designed to evaluate the method; and two histopathological breast cancer sets of whole-slide images used to train the system to predict the presence of tumor metastasis and the tumor proliferation speed.
- Generating saliency maps representing the CNN's areas of interest in the image in order to discover and localize visual cues associated with the image-level labels.

Gigapixel NIC was designed to reduce the size of a gigapixel image while retaining semantic information by shrinking its spatial dimensions and growing along the feature direction.
The method works by, first, dividing the gigapixel image into a set of high-resolution patches. Second, each high-resolution patch is compressed with a neural network (the encoder) that maps every image into a low-dimensional embedding vector. Finally, each embedding is placed into an array that keeps the original spatial arrangement intact so that neighbor embeddings in the array represent neighbor patches in the original image. The encoder network was trained using three well-known families of unsupervised representation learning algorithms :

- Reconstruction Error Minimization : Variational Autoencoder (VAE)
- Contrastive Training
- Adversarial Feature Learning : Bidirectional Generative Adversarial Network (BiGAN)

As a result NIC can exploit visual cues associated with image- level labels successfully, integrating both global and local visual information. Furthermore, they visualized the regions of the input gigapixel images where the CNN attended to, and confirmed that they overlapped with annotations from human experts.
Table 2 summarizes the methodology and results of each deep learning image compression approach.

4. Publicly Available Datasets

In the studies mentioned above, four publicly available histopathology datasets were employed (some for supervised and unsupervised tasks and others for processing tasks) as summarized in Table 3.
We also included the other publicly available digital pathology dataset that could be used for this purpose.

5. Discussion

We have presented image compression techniques for digital pathology slides that can range in size from 1GB to 100GB depending on scanning resolution, making it difficult to transport or duplicate these multi-resolution image files from point A to point B. Cloud infrastructures with integrated storage and computation engines offer a partial answer, but their internal network speed is limited.
As a result, in this paper we examined traditional compression methods and AI approaches for reducing image sizes for sharing between networks or institutions. Actually, the representation and distribution of images with higher quality and lower bit rates, is challenging as well as the memory and computational efficiency in the accurate image.
Lossy compression for WSI can have an impact on the diagnosing process due to information loss, that is why there

was an urgent need for very efficient lossless image compression methods. As a result, lossless image compression is the best way to preserve significant information in images when any sort of data loss is unacceptable.

Therefore, authors intended to investigate the impact of conventional image compression methods (such as JPEG and JPEG2000 being lossless and lossy) on Digital Pathology. These approaches are a region of interest (ROI)-based compression scheme that uses multi-band decomposition via discrete wavelet transform (DWT); it implies that different portions of the image can be saved at different bit rates, resulting in varying image quality. Thus, Its architecture's encoder and decoder are highly sophisticated and expensive.

Also, when compression settings are raised, artifacts seem to be steadily added to an image until they reach a breaking point, at which point the modifications become dramatically severe.

Otherwise, breast tissue proliferates in a variety of ways, ranging from plainly benign to definitively cancerous. On this range, even small compression artifacts make a clear diagnosis impossible. These lacks led the researchers to shift their domain to deep learning algorithms.

Deep learning and, in particular, autoencoders have the potential to outperform the primitive transformations employed in JPEG and other comparable image compression algorithms due to their capacity to generate features from data.

That is why, authors aimed to use CNNs' image-representation capabilities to improve image representation as well as Image Compression. Convolution neural networks (CNN) are particularly excellent at extracting spatial information from images, which is then represented in a more compact manner (essential elements of an image are kept). Their solution not only outperforms the better ways, but it can also take use of parallel computing, resulting in a huge speed increase.

However, there are significant drawbacks to deep learning. The diversity in the data itself is generally one of the biggest challenges to the widespread use of deep learning algorithms in clinical practice (e.g., contrast, resolution, signal-to-noise). Deep learning models typically exhibit poor generalization when employed with input data from multiple computers (different vendors), with varied acquisition parameters, or with any underlying component that might cause the data distribution to shift. With advancements in microscope technology and digital pathology slide scanners, image file sizes and resolution continue to grow, and hence compression of digital pathology slides will remain an open research challenge in the foreseeable future.

6. Conclusions

Conventional lossy image compression methods have been a challenging topic in digital pathology in recent years. Until now, several methods have been proposed for compressing images using deep learning techniques.

Deep Learning is now a popular study topic; its approaches have lately been a research hotspot due to their tremendous learning capacity and advantages in dealing with complicated patterns.

It has piqued the interest of many researchers, and to date, the combination of pre and post processing approaches has become the standard way for image analysis in all study domains, particularly digital pathology.

Table 1. **Summary of conventional image compression methods for digital pathology**

Ref	Year	Dataset	Compression Type	Methdology	Results
[23]	2019	Camelyon16	JPEG2000	Impact of JPEG 2000 compression on a proposed CNN-based algorithm.	**Scenario 1 :** Ratio of 164:1 : F1 score : 0.586 AUC Score : 0.674. **Scenario 2 :** Ratio of 164:1 : F1 Score : 0.934 AUC Score : 0.985. **Scenario 3 :** Ratio of 164:1 :F1 Score : 0.852 AUC Score : 0.944
[10]	2012	Breast Biopsy WSI Slides	JPEG2000	Visual Discrimination Model (VDM)	1:1 mean ROC Az = 0.959 1:8 mean ROC Az = 0.960 1:16 mean ROC Az = 0.959 1:32 mean ROC Az = 0.957 1:64 mean ROC Az = 0.937 1:128 mean ROC Az = 0.877
[14]	2012	Human Tissue & Mouse Embryo	JPEG	Investigation of the lowest Quality Factor (QF) to evaluate and analyse special stained WSI.	The 0.50 m/pixel images at QF 50 or above are suitable for high volume special stained WSI Average Reduction in storage space: From QF 90 to QF 50 is 62.73%.
[5]	2020	**Case1 :** 137 estrogen receptor (ER) –positive breast cancer **Case2 :** Camelyon16 **Case3 :** 100 ER-positive breast cancer	JPEG & JPEG2000	Quantitative Assessment of the Effects of Compression on Deep Learning in Digital Pathology Image Analysis.	**Case 1 :** PSNR of 30 dB as the maximum compression level, compression ratio of 3%. **Case 2 :** PSNR of 22 dB as the maximum compression level, compression ratio of 1%. **Case 3 :** PSNR of 30 dB as the maximum compression level, compression ratio of 7%.
[8]	2018	WSI Data	JPEG2000	Optimized JPEG 2000 Compression for Efficient Storage of Histopathological Whole-Slide Images.	Ratio of 35:1: JP2-WSI is three times more efficient than compressed JPEG 2000.

Table 2. **Summary of digital pathology image compression methods based on deep learning**

Ref	Year	Dataset	Methdology	Results
[16]	2020	Camelyon16	Deep Perceptual Autoencoder (DPA).	AUC: 93.4 in lymph node metastases detection. AUC: 92.6 in abnormal chest X-ray detection.
[21]	2020	Immunohisto-chemistry Images	Stacked Deconvolutional Auto-Encoder-Generative adversarial networks (SDAE-GAN)	AUC Score : 0.73 and Accuracy : 0.72 on cancer liver survival prediction
[12]	2021	PAIP challenge 2019	Histo-Convolutional Auto-Encoder (HCAE)	Accuracy : 0.95 on WSI Tumor Segmentation task at 10x Magnification.
[15]	2020	Camelyon16 Rectum TUPAC16	Neural Image Compression (NIC).	Patch-level classification performance (accuracy) on Camelyon-Tumor : VAE : 0.799 Contrastive : 0.789 BiGan : 0.806 Patch-level classification performance (accuracy) on Rectum-Global : VAE : 0.639 Contrastive : 0.520 BiGan : 0.765

Table 3. **Summary of publicly available digital pathology WSI datasets**

Dataset	Number of Slides	Task
Camelyon16 [1]	400 WSI	Metastasis detection
TUPAC16 [17]	300 WSI	Tumor detection.
Rectum	74 H&E WSI	Rectal Carcinoma Patients
PAIP Challenge	100 WSI	Liver Cancer
TCGA [3]	-	Multiple
BACH [7]	400 WSI	Tissue subtypes classification
ICPR 2014 [6]	50 WSI	Mitosis detection
Cellavision [4]	100 WSI	Cell segmentation

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