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Comprehensive Survey of Classical and Quantum Image Compression Approaches using Neural Networks

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Abstract

The realm of digital signal processing places significant emphasis on image compression, with recent years seeing a surge of interest in neural network-based methods. This survey paper aims to offer a comprehensive review of cutting-edge techniques for image compression that utilize neural networks. The introduction of the study provides an overview of conventional picture compression techniques and their inherent drawbacks. The study then explores the idea of deep learning and how it might be used for picture compression. The survey outlines the various types of neural networks that are utilized for image compression, classifying them based on their compression objective and examining the various training approaches. Furthermore, the paper provides a comparative analysis of several state-of-the-art neural network-based image compression methods by drawing upon literature. This survey paper explores the potential of combining neural networks and quantum computing in the field of image compression, specifically through the use of quantum convolutional neural networks (QCNNs). By leveraging the parallel processing power of quantum computing and the ability of neural networks to recognize patterns in image data, QCNNs offer a promising approach for developing more efficient and effective compression algorithms that preserve image quality while reducing file size. Ultimately, the paper concludes with a summary of the survey, offering insights into the potential of neural network-based image compression for future research. Researchers interested in this area may utilize this survey as a reference.

Keywords Image Compression, Convolutional Neural Networks (CNN), Generative Adversarial Networks (GANs), Quantum CNN, Variational Autoencoders (VAE)

1. Introduction

Image compression is a critical research area due to the ever-growing amount of digital images

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that are being created, stored, and transmitted on the internet. Traditional image compression methods, such as JPEG and PNG (Gersho & Gray, 1992); (Skodras et al., 2001), have been widely used, but they have limitations in terms of achieving high compression rates while preserving image quality. In recent years, deep learning-based approaches have shown promising results in image compression by using neural networks to learn effective representations of images (X. Li et al., 2018) (H. Liu, Chen, et al., 2018) (Mishra et al., 2022a).

This survey paper provides a comprehensive review of the state-of-the-art techniques for image compression using neural networks. We start by providing an overview of traditional image compression techniques and their limitations, followed by an introduction to deep learning and its applications in image compression. We then present a taxonomy of neural network-based compression methods, categorizing them based on the type of neural network used, the compression objective and the training approach.

The paper reviews different types of neural networks used for image compression, including autoencoders (Ballé et al., 2017) (F. Yang et al., 2022) , generative adversarial networks (GANs) (Agustsson et al., 2019a) (Mi et al., 2018) (Zhang et al., 2020) variational autoencoders (VAEs) (Y. Sun et al., 2021) (Y. Yang et al., n.d.) and discusses the strengths and weaknesses of each approach. We also cover different compression objectives, such as rate-distortion optimization, perceptual quality and entropy-constrained compression.

Quantum CNNs are a type of neural network that utilizes quantum computing principles to perform image classification and processing tasks. Quantum computing offers the potential for faster computation and higher parallelization than classical computing, which makes it a promising approach for image processing applications, including image compression (Cong et al., 2019). In 1994, Shor's quantum algorithm utilises a quantum computer to factor integers in polynomial time which was believed to be difficult for traditional computers. In 1995, Grover's algorithm has sparked a lot of interest in search-based techniques(Vogel, 2011). The benefit of quantum computing is that qubits and quantum gates may be used to calculate far more powerful functions(Vogel, 2011) .

One potential application of quantum CNNs in image compression is through the use of quantum algorithms for optimization and feature extraction of images. Quantum computing algorithms such as the quantum approximate optimization algorithm (QAOA) and quantum principal component analysis (PCA) have shown promise in improving optimization and feature extraction in classical CNNs. The application of these algorithms in quantum CNNs for image compression could potentially lead to better compression rates and improved image quality.

Finally, we conclude with a summary of the survey and provide insights into the potential of neural network-based image compression for future research. This survey paper aims to provide a comprehensive and up-to-date overview of the field of image compression using neural networks and to serve as a reference for researchers interested in this area.

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2. Literature Review

Traditional image compression techniques have been studied and utilized for decades. One popular approach is the Discrete Cosine Transform (DCT), which is used in JPEG compression. Another widely-used method is the Discrete Wavelet Transform (DWT), which is employed in JPEG2000 compression (Marcellin et al., n.d.)(Rabbani & Joshi, 2002). These techniques have been extensively researched and have been proven to be effective in reducing the size of image files while retaining a sufficient level of image quality (Dimililer, 2022)(Hu et al., 2020). However, these methods have inherent limitations, such as block artifacts in the case of DCT and high computational complexity for DWT. Therefore, researchers have turned to neural network-based methods for image compression (Nobre & Neves, 2019) .

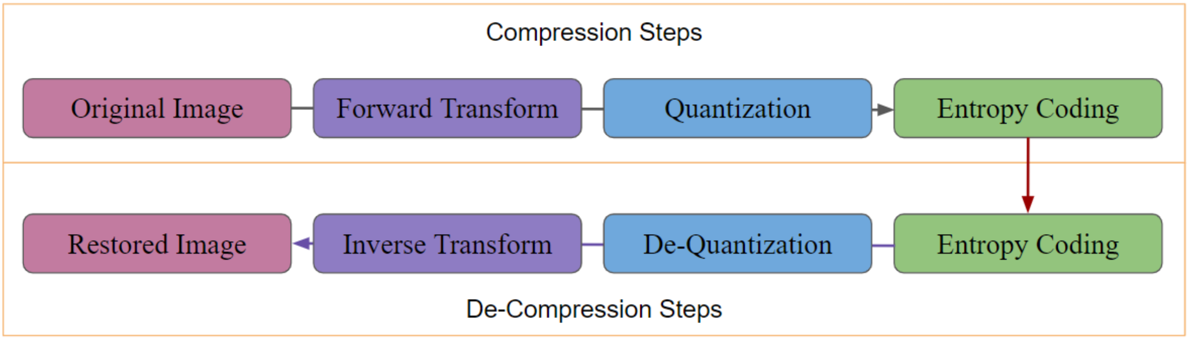

Figure 1: Basics steps in image compression and decompression

Figure 1 shows basic architecture of image compression and decompression. The compression architecture is often made up of an encoder-decoder pair. For the input image z let the distribution is pz, the encoder with quantization function Q and encoding transform ε, generated output as follows:

$$m = Q\big(\varepsilon(z;\varepsilon)\big); \qquad (1)$$

During the learning technique the encoder parameters to be tuned is denoted by $\theta\varepsilon$. To obtain the pixel representation of the image, the corresponding decoder D reconstructs the image ^m from the code m as follows:

$$\hat{x} = D\,\big(Q\big(\varepsilon(z;\varepsilon)\big);\, D\big); \qquad (2)$$

where D represents the parameters in D.

Initial works of image compression using neural networks have shown promising results. In the early stages, researchers used neural networks to learn image transforms that can be used to compress images. However, these methods were not very effective due to the limited capacity of the neural networks at that time. In recent years, with the advancement of deep learning techniques, researchers have been able to develop more powerful neural network-based methods for image compression. These methods typically involve training an autoencoder or a generative adversarial network (GAN) to compress and reconstruct images.

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One notable example is the work by (Toderici et al., 2016) , who proposed a neural network architecture called "End-to-End Optimized Image Compression" (EOIC), which achieved state-of-the-art results on the Kodak image dataset and outperformed previous methods such as JPEG and JPEG2000.

There are several metrics that can be used to evaluate the performance of image compression using neural networks. Here are some of the most commonly used ones:

Peak Signal-to-Noise Ratio (PSNR): This metric measures the difference between the original image and the compressed image in terms of peak signal-to-noise ratio. Higher PSNR values indicate better quality of the compressed image (Z. Li et al., 2021) .

Structural Similarity Index (SSIM): SSIM is a metric that measures the structural similarity between the original image and the compressed image. Higher SSIM values indicate better quality of the compressed image (Abd-Alzhra & Tamimi, 2022) .

Mean Squared Error (MSE): MSE is a metric that measures the average squared difference between the original image and the compressed image. Lower MSE values indicate better quality of the compressed image (Krishna et al., 2016) .

Multiscale Structural Similarity (MS-SSIM): MS-SSIM is a variant of SSIM that measures the structural similarity at multiple scales. This metric is often used to evaluate the quality of compressed images that are designed to work well at different resolutions (Mishra et al., 2022b) .**Bitrate:** Bitrate is a measure of the amount of data required to store or transmit a compressed image. Lower bitrates indicate better compression performance, as less data is required to represent the same image (DU et al., 2022) .

Subjective Quality: Subjective quality measures the perceived quality of the compressed image by human observers. This is often done using subjective tests, where a panel of human evaluators rate the quality of the compressed image on a scale (H. Liu, Chen, et al., 2018) .

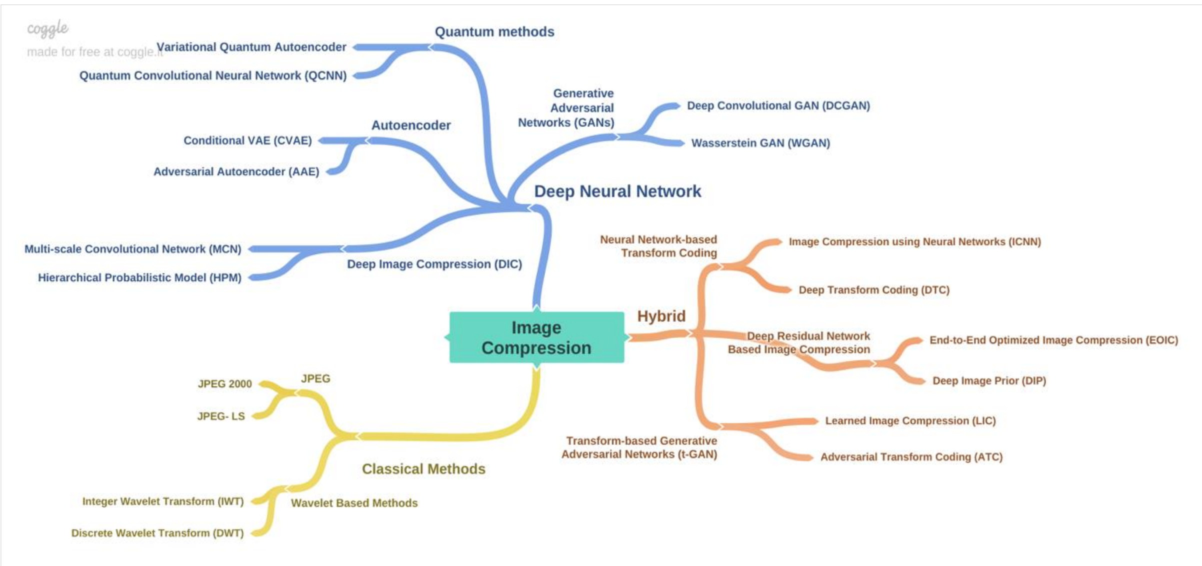

Figure 2: Various research works around image compression field

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Figure 2 is a mind map for image compression using neural networks which includes various interconnected elements. These include different types of neural networks used for image compression, such as convolutional neural networks (CNNs) and autoencoders. Other branches deals about current work done in classical methods.

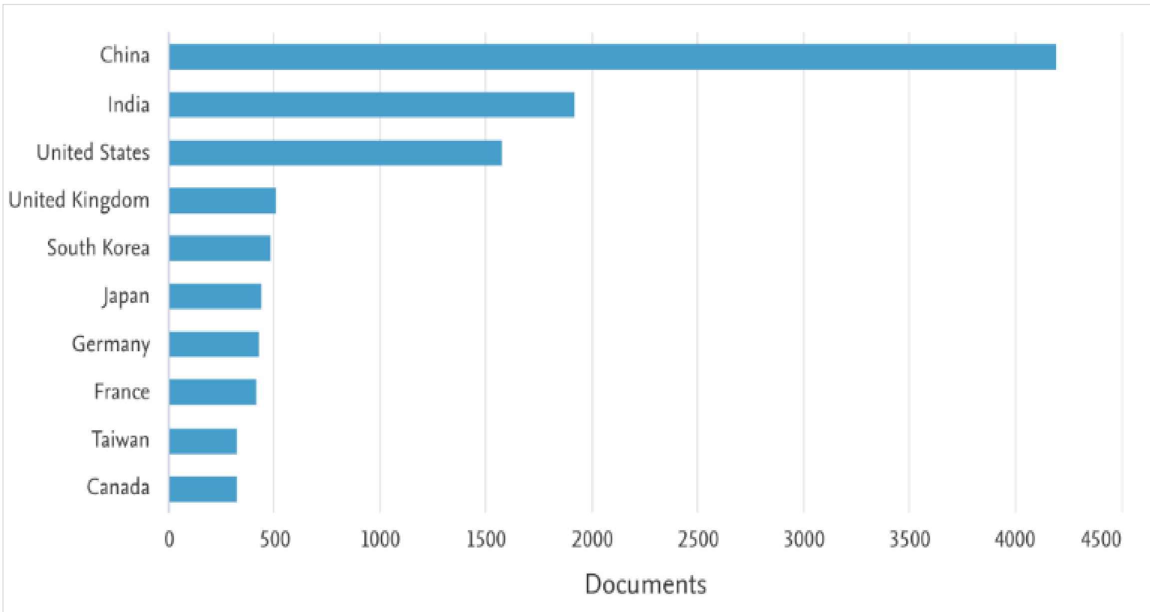

Figure 3: Country wise distribution in terms of works in neural networks - Scopus

Researchers from various countries are actively conducting research in the field of image compression using neural networks as shown in Figure 3. The United States, China, and Europe are some of the leading contributors, with researchers focusing on developing advanced neural network architectures, novel loss functions and optimization algorithms, and new techniques

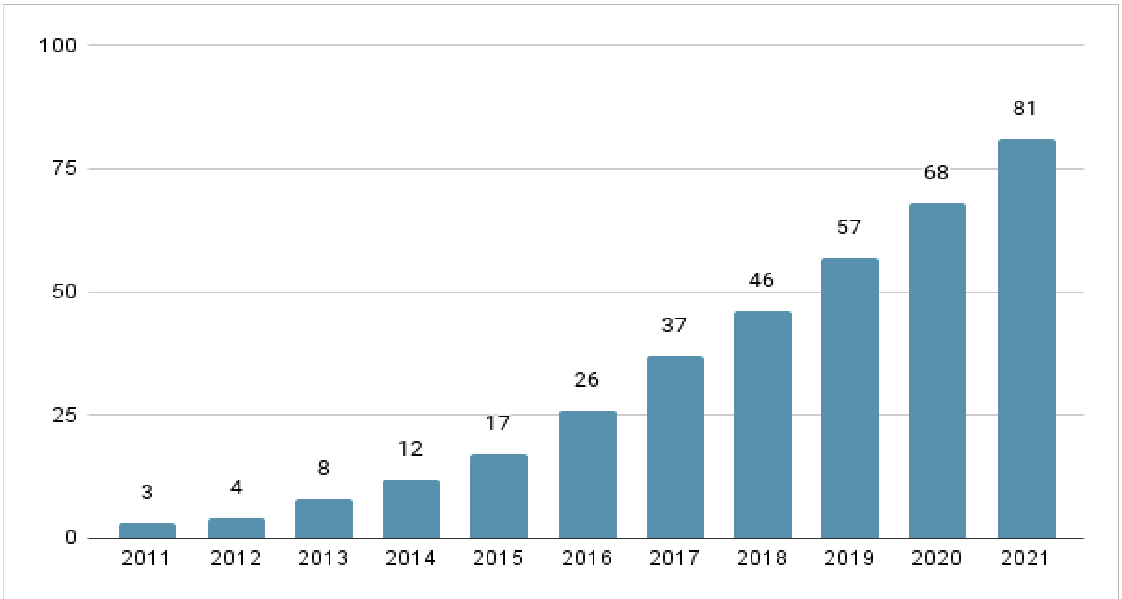

Figure 4: Number of research in neural network-based image compression

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r input data preprocessing. Researchers from Japan, India, and Canada are also making significant contributions by exploring the use of deep learning techniques, hybrid neural networks, and video compression, respectively. The collaborative efforts of researchers from different countries are crucial for advancing the field of image compression using neural networks and driving innovation in computer vision.

2.1. Image Compression Using Neural Network Techniques

Image compression using neural networks is a technique that involves using deep learning models to compress images while minimizing the loss of image quality. Neural networks are trained to learn the underlying patterns in image data, which can be used to selectively discard or retain certain image features during the compression process. This results in a compressed image that takes up less storage space while still retaining the key visual information (Hussain et al., 2018) . Figure 4 shows numbers of research papers are increasing YoY to adapt newer technologies.

2.2. Convolutional Neural Networks (CNNs)

CNNS are particularly well-suited for image compression, as they are designed to recognize patterns in visual data and can learn to identify the most important image features for retention. CNNs can also be trained to selectively discard less important features, resulting in a compressed image that still retains the important visual information. This makes CNN-based image compression particularly useful in applications where storage space is limited, such as in mobile devices or in transmission over networks with limited bandwidth (Jamil et al., n.d.). CNNs are designed to recognize patterns in visual data by using convolutional layers to extract local features and pooling layers to reduce dimensionality. In the context of image extraction, (Y. Li et al., 2019) CNNs can be used to isolate specific objects or regions of interest within an image, or to extract information about the image as a whole. This process can be useful in a variety of applications, such as object recognition, scene segmentation, and image classification (H. Liu et al., 2020) . Below are steps of architecture details for knowledge extraction using CNN as show in Figure 5.

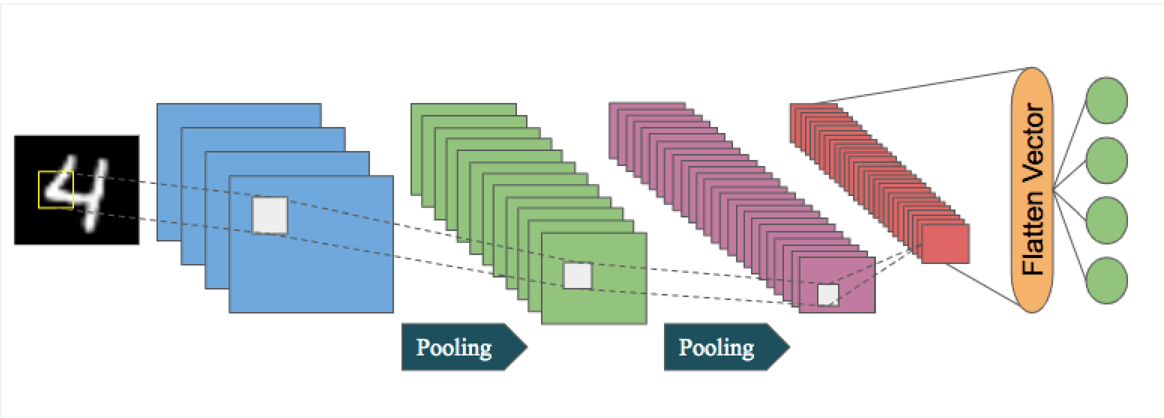

Figure 5: Image features extraction using convolutional layers

Input layer: The input layer of a CNN takes in the image data, which is typically preprocessed

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to a fixed size and format.

Convolutional layers: Convolutional layers are the backbone of a CNN, where a set of learnable filters are applied to the input image to extract local features. These filters slide over the entire image, capturing patterns such as edges, corners, and textures.

Pooling layers: Pooling layers are used to down sample the feature maps produced by the convolutional layers, reducing the dimensionality of the input while retaining important features.

Fully connected layers: Fully connected layers are used to classify the extracted features into specific classes or categories. These layers connect every neuron in one layer to every neuron in the next layer, producing a high-level representation of the image.

Output layer: The output layer produces the final output of the CNN, which can be a set of class probabilities, a segmentation mask, or a feature vector.

There are several CNN architectures that have been proposed for image compression, each with its own strengths and weaknesses. (Mishra et al., 2022a) Some popular architectures include Autoencoders, Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Transform-based CNNs such as JPEG and HEVC(Abd-Alzhra & Tamimi, 2022) (D. Liu et al., 2021) . These architectures vary in their approach to image compression, with some focusing on lossy compression and others on lossless compression. Each architecture has its own set of advantages and limitations, and the choice of architecture depends on the specific requirements and constraints of the application (Mishra et al., 2022a).

2.3. Autoencoders

Autoencoder-based image compression has become a popular approach in recent years.

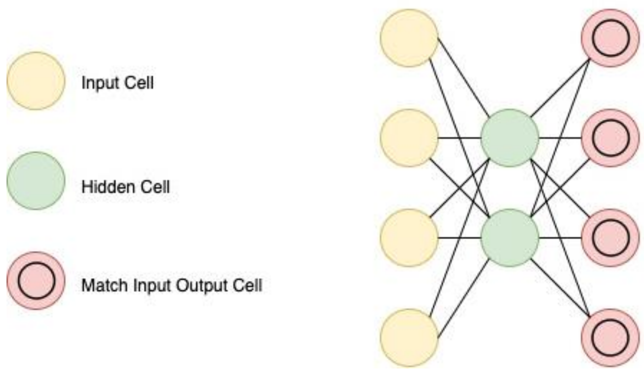

Figure 6: Network architecture of autoencoder

Figure 6 is the architecture of autoencoder typically consists of an encoder network, which transforms the input data into a compressed representation, and a decoder network, which reconstructs the original input from the compressed representation. Autoencoders are neural networks that learn to encode and then decode an input image, aiming to reconstruct the original

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image as closely as possible. (Doersch, 2016) By setting a bottleneck layer in the network, the autoencoder can reduce the dimensionality of the input data, thereby compressing the image (Theis et al., 2017). This approach has been shown to outperform traditional compression techniques such as JPEG and JPEG2000 in terms of image quality at low bitrates. Several variants of autoencoders have been proposed for image compression, including convolutional autoencoders (CAEs) (Jamil et al., n.d.) and generative adversarial networks (GANs) (Agustsson et al., 2019a). Researchers have also explored incorporating perceptual metrics into the loss function of the autoencoder to enhance the quality of the reconstructed image. For instance, the method proposed by (Agustsson et al., 2019a) achieved a 44:1 compression ratio while maintaining the image quality comparable to JPEG at 10:1 compression ratio. (Mi et al., 2018) proposed a deep autoencoder that learns codewords and residuals for image compression. Their method achieved better performance in terms of image quality compared to traditional compression methods such as JPEG. (Z. Chen et al., 2018) presented a progressive content-based layer-by-layer optimization method for deep neural network compression that significantly reduces the size of the network. (H. Liu, Wang, et al., 2018) explored using deep convolutional neural networks (CNNs) to preserve image fidelity against extreme JPEG compression. They proposed a CNN-based approach that improves the visual quality of compressed images by removing compression artifacts.

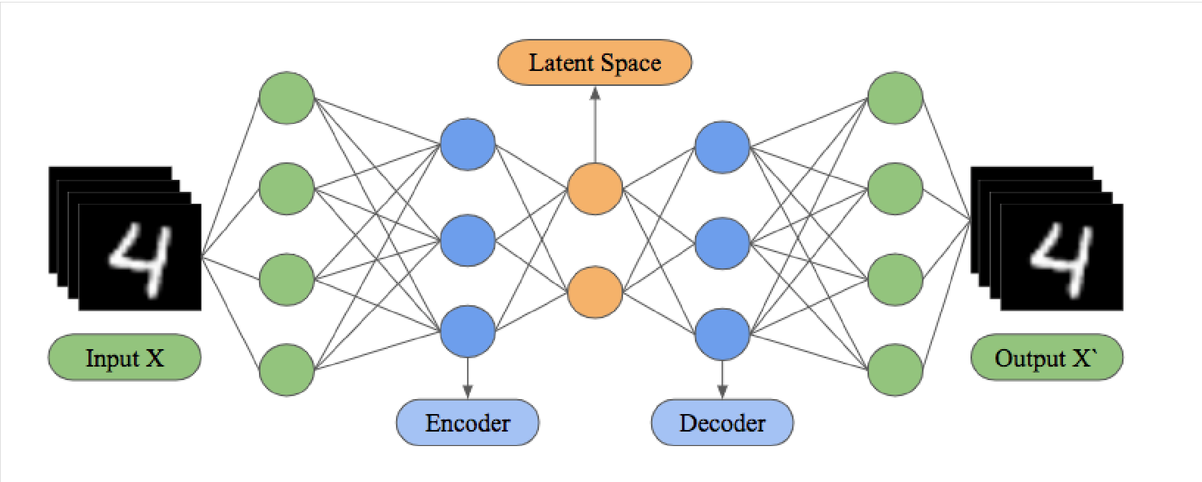

Figure 7: Network architecture of autoencoder based image compression

Figure 7 shows the encoder and decoder components of the architecture. The encoder network typically consists of several fully connected layers or convolutional layers, while the decoder network is typically a mirror image of the encoder network. The autoencoder is trained to minimize the difference between the input and output data, which encourages the network to learn a compressed representation that captures the most important features of the input data.

Autoencoders are a popular tool for image compression due to their ability to learn compact representations of input images. However, there are several gaps in the current state-of-the-art approaches for image compression with autoencoders. One major gap is the trade-off between compression rate and image quality (Litjens et al., 2017) . While current methods can achieve

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high compression rates, they often result in images that are visually distorted or of low quality. This is a significant limitation in applications where image quality is critical, such as medical imaging or remote sensing.

Another gap is the lack of robustness of current methods to variations in image content and size. Autoencoder-based compression methods often assume that the input images have similar characteristics and are of fixed size (Mishra et al., 2022a). However, real-world images can vary significantly in content and size, making it challenging to apply these methods to a wide range of applications.

Finally, there is a need for more efficient training and optimization methods for autoencoder-based compression. Current methods often require large amounts of training data and computational resources, making them impractical for many real-world applications.

2.4. Variational Autoencoders

Variational Autoencoder (VAE) is a deep learning architecture that can be used for image compression. The VAE approach learns a compressed representation of images by encoding the images into a lower-dimensional space, known as a latent space. The compressed image can then be reconstructed by decoding the latent space representation back into the original image space. Variational autoencoders (VAEs) are a type of autoencoder that incorporate probabilistic modeling into the latent space. In VAEs, the encoder maps the input image to a probability distribution in the latent space, rather than a single point as in a regular autoencoder. This probabilistic approach allows the VAE to generate new images by sampling from the latent space distribution. The decoder then maps the sampled latent representation back to the original image space. The use of probabilistic modeling in VAEs for image compression has been explored in studies such as the work by (Ballé et al., 2016) (Ballé et al., 2017) on image compression with variational autoencoders.

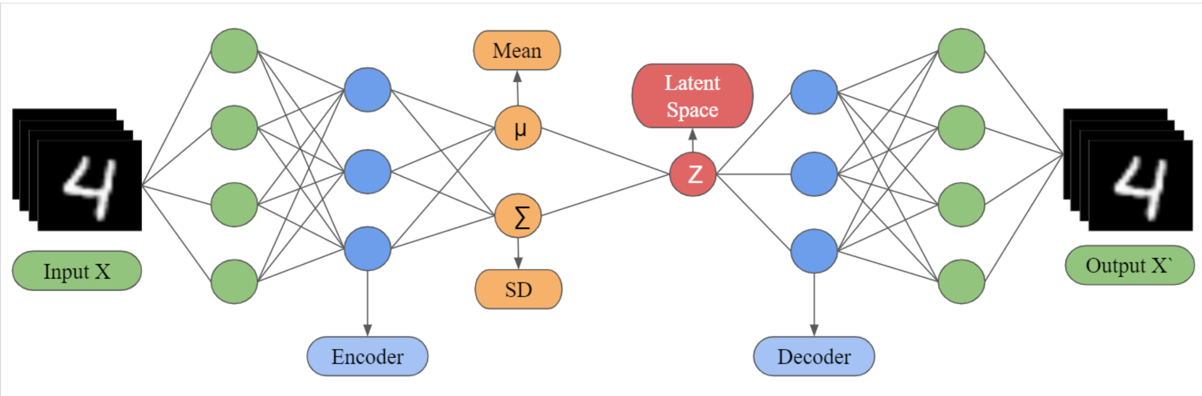

Figure 8: Working of VAE for image compression and decompression

Figure 8 shows architecture of VAE. The encoder network learns to approximate the true posterior distribution of the latent variables given the input data. This allows VAEs to generate new samples from the learned distribution in the latent space, which can be used for applications such as image generation and data synthesis.

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Several studies have demonstrated the effectiveness of VAE for image compression. For instance, in a study by (X. Li et al., 2018) the authors used a VAE to compress high-resolution images and achieved a compression rate of up to 200:1, while maintaining high visual quality. Similarly, (W. Chen et al., 2020) used a VAE-based compression method to achieve a high compression rate on large-scale image datasets with minimal loss of image quality.

Furthermore, VAE-based compression has also been shown to be effective in real-time applications. In a study by (Jing et al., 2021) the authors proposed a VAE-based method for compressing video frames in real-time, achieving a high compression rate with low computational cost. In summary, VAE is a powerful approach for image compression, which has been demonstrated to achieve high compression rates while maintaining image quality. Moreover, VAE-based compression methods can be adapted for real-time applications with low computational cost, making it a promising approach for various practical scenarios.

Despite the promising results of VAE for image compression, there are still several research gaps in this area. Some of the current research gaps include:

One of the significant computational research gaps in VAE for image compression is the high computational cost of the training process. Training VAEs on large image datasets can take a considerable amount of time, making it difficult to scale the approach to real-world applications. For example, (X. Li et al., 2018) noted that their VAE-based compression approach required a long training time, even with the use of GPU acceleration. Similarly, (W. Chen et al., 2020) mentioned the challenge of training VAEs on large-scale image datasets due to the high computational cost. Several techniques have been proposed to address this computational research gap, such as using parallel computing and GPU acceleration to speed up the training process. However, there is still a need for more efficient training techniques, particularly for large-scale image datasets.

Another computational research gap is the difficulty in optimizing the hyperparameters of VAEs. Hyperparameters, such as the number of layers, the size of the latent space, and the learning rate, can significantly affect the compression quality and training time. However, finding the optimal set of hyperparameters can be time-consuming and computationally expensive, especially for large-scale datasets. (Zhao et al., 2021) highlighted the importance of optimizing the hyperparameters of VAEs for efficient compression. The authors noted that finding the optimal set of hyperparameters can be computationally expensive, particularly for large-scale video datasets. They proposed a context-adaptive entropy model to address this computational research gap and improve the compression efficiency of VAE-based methods. To address this computational research gap, researchers can explore new techniques for optimizing the hyperparameters of VAEs, such as using Bayesian optimization or evolutionary algorithms (Mi et al., 2018) . These techniques can help to reduce the computational cost of finding the optimal hyperparameters.

In summary, the computational research gap in VAE for image compression includes the high computational cost of training and difficulty in optimizing hyperparameters. Addressing these

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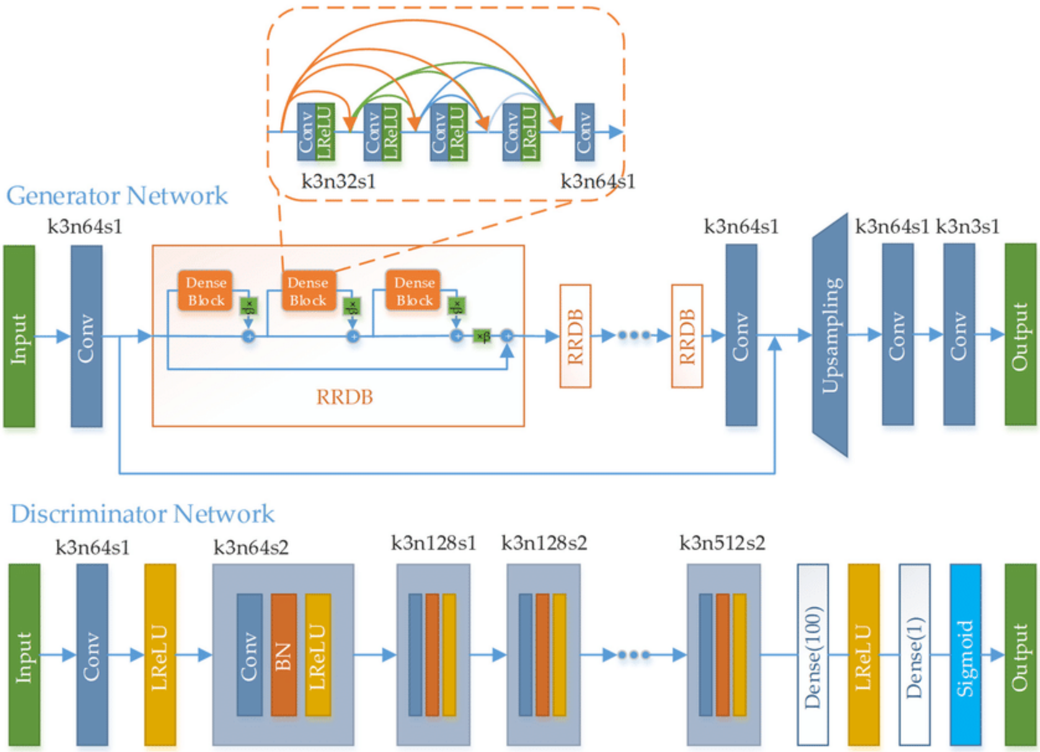
computational research gaps is crucial for making VAE-based compression methods more practical and scalable for real-world applications.

2.5. Generative Adversarial Networks

Image compression using GAN (Generative Adversarial Networks) is a promising research area that has gained significant attention in recent years. GAN-based image compression methods aim to learn a compressed representation of the input image using a generator network, which is trained in an adversarial manner with a discriminator network. One of the significant advantages of GAN-based image compression is the ability to generate high-quality reconstructed images with low bitrates (Agustsson et al., 2019a)(Mishra et al., 2022a). GAN-based compression methods can achieve better compression quality compared to traditional compression methods such as JPEG or MPEG. Moreover, GAN-based compression methods can handle complex images such as natural scenes, textures, and patterns. Several GAN-based compression methods have been proposed in recent years, including GAN-based compression with entropy coding, GAN-based compression with skip connections, and GAN-based compression with spatial attention mechanisms (Mi et al., 2018) (Zhang et al., 2020). These methods have shown promising results in terms of compression quality and reconstruction fidelity.



(H. Chen et al., 2019)

Figure 9: Working of GAN

Figure 9 shows the architecture diagram of Generative Adversarial Networks. The architecture consists of two networks: a generator network that generates fake data samples and a

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discriminator network that tries to distinguish between the generated samples and real data samples from the training set. The two networks are trained together in an adversarial process, where the generator network tries to create samples that can fool the discriminator network, and the discriminator network tries to correctly classify the real and fake samples. Through this process, the generator network learns to generate increasingly realistic samples, while the discriminator network becomes more accurate at distinguishing real and fake samples.

The use of Generative Adversarial Networks (GANs) for image compression is a relatively new area of research, with the first works appearing in the early 2010s. One of the early works in this area was by (Toderici et al., 2016), who proposed a GAN-based method for compressing images that achieved visually pleasing results with a compression ratio of 16:1 on average. Since then, there have been several other works exploring the use of GANs for image compression, with promising results. For example,(Agustsson et al., 2019a) proposed a scalable image compression method using generative adversarial networks (GANs). They trained a GAN to compress images by learning a mapping from the uncompressed image space to the compressed space.(Agustsson et al., 2019a) proposed a method called "Generative Compression" (GC) that uses a GAN to compress images in a way that allows for efficient decoding and reconstruction. The method achieved competitive results on standard image compression benchmarks and was able to generate visually appealing images with high compression ratios (Agustsson et al., 2019b). Finally, (Y. Yang et al., n.d.) introduced a perceptual loss function for enhancing the quality of reconstructed images in autoencoder-based compression. They demonstrated that incorporating perceptual metrics into the loss function can significantly improve the perceptual quality of compressed images. Overall, these studies demonstrate the potential of autoencoder-based methods for image compression and provide valuable insights for further research in this area.

However, there are still several research gaps in GAN-based image compression, including the high computational cost of training GANs, the difficulty of controlling the compression rate, and the sensitivity to noise and perturbations in the input image. Addressing these research gaps is crucial for making GAN-based compression methods more practical and scalable for real-world applications. In summary, GAN-based image compression is a promising research area that has shown to achieve high compression quality and handle complex images. However, there are still several research gaps that need to be addressed to make GAN-based compression methods more practical and efficient.

2.6. Quantum CNN

Conventional deep neural networks have grown in popularity over the last decade and are currently among the most essential and well-known machine learning technologies.

Deep feed-forward networks are the most fundamental type of classical deep neural networks and may be formally stated as in equation

$$v = f(x; \theta) \qquad (3)$$

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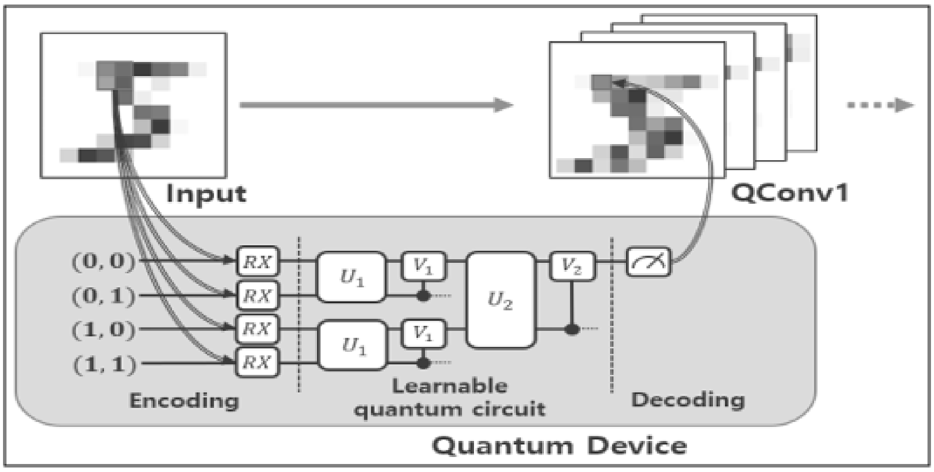
Here v represents the created output vector of m dimensions, and theta represents the essential parameters for mapping the input vector to the output vector. x represents the n-dimensional input vector.(Courville, 2016)

The drawback of convolutional neural networks (CNN) is when the data or model dimension is excessively vast, they learn ineffectively. As a result, (Oh et al., n.d.) demonstrated how to combine classical CNN and quantum processing to create a method that is more effective and outperforms the competition and can be used to tackle challenging machine learning problems.

Figure 10 shows how the convolution layer and the pooling layer, are applied to quantum systems in the QCNN model. The idea develops as follows:

- By applying several qubit gates to neighboring qubits, the convolution circuit is able to detect the hidden state.
- By monitoring the proportion of qubits or implementing 2-qubit gates like CNOT gates, the pooling circuit minimizes the size of the quantum system.
- Repetition of the pooling and convolution circuits seen in above Figure The completely linked circuit can be utilized as a latent representation when the system is small enough.



(Source: A Tutorial on Quantum Convolutional Neural Networks (QCNN) (Oh et al., n.d.))

Figure 10: Quantum convolution layer

Superposition and parallel computation, which do not present in traditional computers, are advantages of quantum computing that can shorten learning and testing times. Existing quantum computers can only handle tiny quantum systems, though. Small quantum computers can build the quantum convolution layer because it processes the image map as much as the filter size at a time rather than applying the entire image map to a quantum system at once (Oh et al., n.d.).

2.7. Quantum Inspired Neural Networks

Quantum neural networks (QNNs) offer several benefits in terms of computational power

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compared to classical neural networks. QNNs leverage quantum computing principles such as quantum entanglement, superposition, and interference to perform computations that would be intractable for classical computers. QNNs can solve problems exponentially faster than classical neural networks for certain tasks, such as optimization problems and matrix inversion (Cong et al., 2019)(Farhi & Neven, 2018). Moreover, QNNs can learn more efficiently from limited data, making them particularly useful for applications such as drug discovery, financial modeling, and traffic forecasting. However, QNNs are still in the early stages of development, and there are several challenges to overcome, such as hardware limitations and algorithmic design. Nonetheless, the potential benefits of QNNs make them an exciting area of research for improving the computational power of neural networks.

Quantum convolutional neural networks (QCNNs) offer several advantages over classical CNNs. QCNNs can leverage the computational power of quantum computing to perform computations exponentially faster than classical CNNs for certain tasks (Cong et al., 2019). This makes QCNNs particularly useful for applications such as image and video recognition, where large amounts of data need to be processed quickly. Additionally, QCNNs can learn more efficiently from limited data, making them useful for applications such as medical imaging and satellite imagery analysis. Furthermore, QCNNs can potentially improve the security of image and video processing applications through quantum encryption techniques. However, QCNNs are still in the early stages of development, and there are several challenges to overcome, such as the need for more powerful quantum hardware and improved algorithmic design. Nonetheless, the potential advantages of QCNNs make them an exciting area of research for improving the performance of CNNs.

Quantum Convolutional Neural Networks (QCNNs) are a class of neural networks that utilize quantum computing principles to perform convolution operations. QCNNs can exploit quantum entanglement and interference to speed up computation compared to classical CNNs. QCNNs can be implemented using quantum circuits that are composed of quantum gates, such as the controlled-NOT gate and the Hadamard gate (Huang et al., 2021). The output of the QCNN can be read out using quantum measurements. Several QCNN architectures have been proposed in recent years, including the Quantum Convolutional Neural Network (QConvNet) and the Quantum Image Processing (QIP) model. QCNNs have shown promising results in image and video processing applications, including image recognition, object detection, and video classification. However, QCNNs are still in the early stages of development, and there are several challenges to overcome, including the need for more powerful quantum hardware and improved algorithmic design. Nonetheless, the potential advantages of QCNNs make them an exciting area of research for improving the performance of CNNs. Figure 11 shows architecture of hybrid network with fully connected layers. A typical hybrid QCNN architecture consists of a classical neural network with one or more fully connected layers, followed by a quantum circuit that processes the data using quantum gates.

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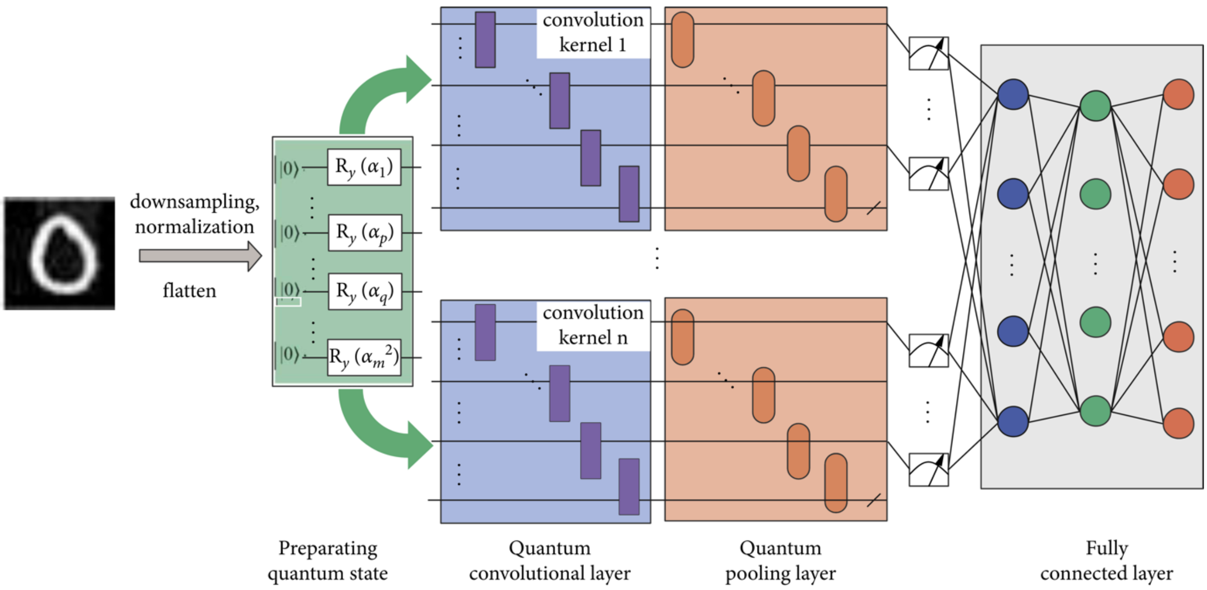

Figure 11: Hybrid network of using QCNN with fully connected layer (W. Li et al., 2022)

There are potential benefits to using Quantum Convolutional Neural Networks (QCNNs) in image compression with Variational Autoencoders (VAEs) (H. Liu et al., 2020) (Xu et al., 2021). QCNNs can leverage the computational power of quantum computing to perform computations faster than classical CNNs, which could potentially lead to faster compression and decompression of images. Additionally, (Cong et al., 2019)(Dallaire-Demers & Killoran, 2018) QCNNs can learn more efficiently from limited data, which is a crucial factor in VAE-based image compression where the compression model needs to be trained on a limited dataset. Moreover, QCNNs can potentially improve the security of image compression through quantum encryption techniques. However, research on QCNN-based VAE for image compression is still in its early stages, and there are several challenges to overcome, such as the need for more powerful quantum hardware and improved algorithmic design. Nonetheless, the potential benefits of using QCNNs with VAEs make them an exciting area of research for improving the performance of image compression algorithms (Romero & Aspuru-Guzik, 2021) .Recent Works

Some of the recent work in image compression is listed below

Study	Keywords	Year
Region-of-interest and channel attention-based joint optimization of image compression and computer vision (B. Li et al., 2022)	Attention; Computer vision; Learned image compression; ROI bit allocation	2022
Successive learned image compression: Comprehensive analysis of instability (Kim et al., 2022)	Deep learning; Image compression; Successive image compression	2022
Image Forgery Detection Using Deep learning	Convolutional neural networks; Forgery detection; Image	2022

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by Recompressing Images (Ali et al., 2022)	compression; Image processing; Neural networks	
Image Compression Using Stochastic-AFD Based Multisignal Sparse Representation (Dai et al., 2022)	Image compression; Image reconstruction; Sparse representation; Stochastic adaptive Fourier decomposition	2022
DCT-based medical image compression using machine learning (Dimililer, 2022)	DCT image compression; Machine learning; Medical imaging; Optimum image compression	2022
Region-of-interest and channel attention-based joint optimization of image compression and computer vision (B. Li et al., 2022)	Attention; Computer vision; Learned image compression; ROI bit allocation	2022
Deep-learning with context sensitive quantization and interpolation for underwater image compression and quality image restoration (Nair & Domnic, 2022)	C-CNN; Contrast Sensitivity Function; Convolutional Neural Networks; JPEG; RD-CNN; Underwater image compression	2022
Region-of-interest and channel attention-based joint optimization of image compression and computer vision (B. Li et al., 2022)	Attention; Computer vision; Learned image compression; ROI bit allocation	2022
Image Compression Using Deep Learning: Methods and Techniques (Abd-Alzhra & Tamimi, 2022)	Auto Encoders; Deep learning; Image Compression; JPEG; JPEG2000; Lossless; Lossy; MS-SSIM; PSNR; SSIM	2022
Image compression optimized for 3D reconstruction by utilizing deep neural networks (Golts & Schechner, 2021)	3D reconstruction; Deep learning; Image compression; Recurrent neural networks	2021
Universal discriminative quantum neural networks (H. Chen et al., 2021)	Quantum computing; Quantum data classification; Quantum machine learning; Quantum sensing	2021
Quantum generative models for data generation (T. P. Sun et al., 2021)	Quantum advantage; Quantum generative models; Quantum machine learning	2021
Variational Quantum Generators: Generative Adversarial Quantum Machine Learning for Continuous Distributions (Romero & Aspuru-	generative adversarial network; generative modeling; machine learning; quantum computing;	2021

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Guzik, 2021)	variational quantum algorithms	
Comparison of Full-Reference Image Quality Models for Optimization of Image Processing Systems (Ding et al., 2021)	Image quality assessment; Perceptual optimization; Performance evaluation	2021
Quantum Convolutional Neural Networks for Image Processing (Cai et al., 2021)	QCNN	2021
Distributed compression and decompression for big image data: LZW and Huffman coding (Netalkar et al., 2021)	Huffman coding; Lempel; SPARK; Welch; Ziv; compression; decompression; distributed system	2021
Efficient and Effective Context-Based Convolutional Entropy Modeling for Image Compression (M. Li et al., 2020)	Context-based convolutional networks; entropy modeling; image compression	2020
Deep OCT image compression with convolutional neural networks (Guo et al., 2020)	Image compression; Image processing; Image quality; Image storage; Medical image processing; Neural networks	2020
Image compression with encoder-decoder matched semantic segmentation (Hoang et al., 2020)	Index Terms-Semantic segmentation; learning-based compression; semantic enhancement	2020
A Tutorial on Quantum Convolutional Neural Networks (QCNN) (Oh et al., n.d.)	QCNN	2020
Deep Learning-Based Picture-Wise Just Noticeable Distortion Prediction Model for Image Compression (H. Liu et al., 2020)	Just noticeable distortion; convolutional neural network; image quality assessment; visual perception	2020

3. Research Gaps and Opportunities for Future Work

Despite the success of neural network-based image compression methods, there are still several research gaps that need to be addressed. Some of the current research gaps in image compression with neural networks include:

Limited interpretability: Neural network-based image compression methods lack interpretability, which makes it challenging to understand how the model generates compressed images. Developing interpretable models could help increase trust and confidence in these algorithms.

Limited generalization: Neural network-based image compression methods often struggle

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with generalizing to unseen data. Developing algorithms that can generalize better to different image types and sizes could help make these algorithms more practical.

Trade-off between compression ratio and image quality: Finding the right balance between compression ratio and image quality remains a challenge in neural network-based image compression. Developing methods that can provide high compression ratios while maintaining good image quality is an ongoing area of research.

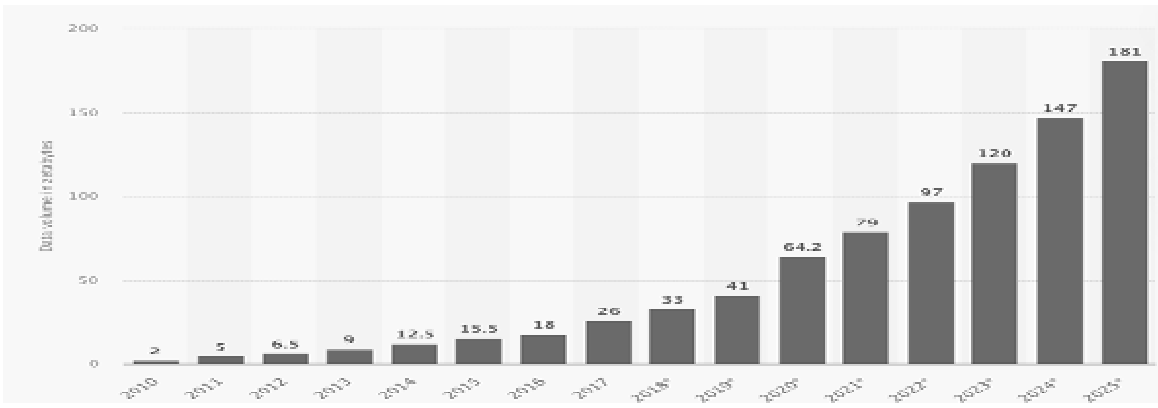
Limited scalability: Neural network-based image compression methods can be computationally intensive, which limits their scalability. Developing algorithms that can handle large-scale datasets and operate efficiently on a wide range of hardware could make these algorithms more practical for real-world applications.

Limited security: Neural network-based image compression methods can be vulnerable to adversarial attacks, which can compromise the security of compressed images. Developing methods that can improve the security of these algorithms is an important area of research.

Below research gaps describes ore business use cases in real world applications.

Global Cloud Storage

Today there might be trillions of images that had been stored in cloud drives such as gmail, google drive. This requires more robust compression technique which will help optimize space for across all domains. The traditional compression codes cannot help in such scenarios. A more powerful compact representation is required to solve this problem on large scale. Data transmission is also affected with more content being transmitted across network, ex. OTT platform like Amazon Prime, Netflix stream high resolution content.



Source: (Statista Research Department, 2022)

Figure: Volume generate and forecasted till 2024 in zeta bytes

Global Optimization for traditional codecs

The conventional hybrid picture codecs, which are still commonly used, have drawbacks. First,

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the foundation of each of these methods segregate blocks of images, incorporates blocking consequences. Second, the codec's modules are intricately dependent on one another. Consequently, being challenging to conjunctionally enhance the entire codec. Third, because entire model cannot be enhanced, it may be difficult to further enhance the complex framework because a change to one module alone may not enhance the model as a whole.

Standardization of Neural Network Framework

There are various versions of variational auto-encoder which are been research upon. This are still in beginning phase and more research is required in this area. There is dire need to have standard architecture (like JPEG) which can be implemented across domains (B. Li et al., 2022)(F. Yang et al., 2022). As of today, even small change in neural architecture requires retraining of network which requires huge computational power.

Full-Resolution Image Processing

Convolutional neural networks make it possible to process pictures in their whole, whereas hybrid frameworks usually process them in segments. Entropy modelling with additional information and avoiding the effect of blocking brought on due to partitioning may benefit from processing. Additionally, full resolution processing involves a rise in complexity. Convolutional kernels have a constrained perceptual field, therefore to sense more big regions and increase modelling capability, the network must be deeper. Deepening CNN layers will increase number of learning parameters which will increase training time and increase in computational consumption.

Aliasing Effect in Reconstructed Image

The aliasing effect of learned lossy image compression frameworks on the recreated image. A phenomenon known as aliasing occurs when the directionality of the patterns in the reconstructed pictures produced by CNN and CAE based architectures changes. Due to this issue deployment of neural network architecture becomes extremely difficult.

QML a new technology that is being widely used to automate many jobs, provides numerous benefits over traditional machine learning (Rebentrost et al., 2014). QML has the ability to handle large amounts of data effectively and achieve exponential speedups in many applications. Medical arena, picture compression, predicting series, and spam identification are few applications of QML (Xia & Kais, 2018) (Sergioli et al., 2019)(Sagheer et al., 2019). It may also be used to tackle scheduling and classification problems with great accuracy and efficiency. Other domain applications are detection of cervical cancer, electro cardiac signals classification, speech recognition etc. Quantum computation's great speed and efficiency, it can be used efficiently in real-time applications.

4. Conclusion

In conclusion, neural network-based image compression algorithms have shown promising results in recent years. These algorithms leverage the power of deep learning and have demonstrated superior performance compared to traditional image compression methods.

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Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs) are some of the most popular neural network architectures used in image compression. CNNs are widely used for image compression due to their ability to learn local features from images. GANs and VAEs, on the other hand, are used for generative image compression, where the model generates compressed images from latent variables. Despite their success, there are still challenges to be addressed, such as balancing compression ratio and image quality, dealing with large-scale datasets, and improving the efficiency of training and inference.

The future of quantum computing in the field of image compression using neural networks is promising. Quantum computing has the potential to significantly speed up image compression algorithms by performing complex calculations in parallel. This could lead to more efficient and effective compression methods that preserve the quality of the images while reducing their size. As quantum computing technology continues to advance, we can expect to see exciting new developments in the field of image compression that leverage the power of both quantum computing and neural networks. Nonetheless, the future of image compression using neural networks is promising, and there is a lot of room for further research and development in this field.

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