

An AI-Driven Deep Autoencoder-Based Image Compression Framework for Optimizing Storage and Retrieval of Digital Content in Information Systems

Sivakumar R.D.¹ and Ruba Soundar K²

¹Assistant Professor (Senior Grade), Post Graduate Department of Computer Applications, Mepco Schlenk Engineering College, Sivakasi.

²Associate Professor (Senior Grade), Department of Computer Science and Engineering, Mepco Schlenk Engineering College, Sivakasi.

E-mail – ¹rdsivakumarstaff@gmail.com

ARTICLE INFO

Received: 21 Aug 2024

Accepted: 04 Nov 2024

Published: 04 Dec 2024

ABSTRACT

In today's information systems, digital content has grown so much that storing data, transferring it and accessing multimedia resources in a timely fashion have become a problem. To meet these challenges, image compression is a key component in minimizing storage space needed while maintaining reasonable image quality. The study has introduced an AI-based Deep Autoencoder Based Image Compression Framework that can optimize storage and retrieval of digital content in information systems. The framework is based on a deep autoencoder network, which learns compact and meaningful representations of image data, allowing for efficient compression and reconstruction. The proposed method differs from the existing image compression methods as it uses artificial intelligence to automatically extract salient image features and reduce redundant information to gain benefits in terms of compression without sacrificing much in terms of visual quality. Typical test image sets and common performance measures, such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), and Bits Per Pixel (BPP), are used for evaluating the effectiveness of the framework. The experimental results show that the proposed deep autoencoder model outperforms the traditional compression schemes in terms of compression efficiency with good image quality and structural similarity. Besides that, the structure can improve the storage efficiency and provide quicker access to digital information, thus applicable to large scale information systems handling large multimedia repositories. Incorporating AI into image compression enhances the scalability, resource utilization, and accessibility of content within large data sets. The proposed framework can be effectively used in a digital library, educational repository, cloud-based storage system, enterprise information systems, and multimedia content management system. The results show that using deep learning for image compression is a promising approach to meet the challenge of efficiently managing digital information, and is also important for the sustainable and intelligent operation of information systems in the age of massive digital data.

Keywords: Artificial Intelligence, Deep Autoencoder, Image Compression Framework, Digital Content Management, Information Retrieval, Information Systems, Multimedia Data Compression, Storage Optimization, Deep Learning, Performance Evaluation.

INTRODUCTION

Background of the Study

With the digital technologies rapidly evolving, and the general acceptance of information systems, the amount of digital content has increased across many sectors such as education, healthcare, business, entertainment and social media. Today, organizations use digital images, multimedia files, and visual resources for communication, documentation and decision making processes, and this creates huge amount of data that is generated and stored every day. With the ever increasing amount of digital information, information systems have great storage space, bandwidth utilization, and effective content retrieval challenges. Conventional storage systems can be inefficient at scaling to handle massive image libraries and provide satisfactory performance. Efficient storage and retrieval mechanisms are therefore critical to reduce the data redundancy and optimize resources usage. To address these issues, image compression has become a key enabler in the field of digital content management and information systems, enabling the efficient storage, transmission, and processing of digital images, which has greatly improved the performance and scalability of these systems.

Problem Statement

As the volume of digital images continues to increase in contemporary information systems, the management of their storage, their transmission and retrieval of their contents are becoming a problem. The ever growing size of image datasets collected in the context of education, digital libraries, health care, social media, and enterprise information systems is accompanied by significant storage space and bandwidth requirements, leading to high operational expenses and compromising system efficiency. To overcome these problems, many traditional image compression methods have been used such as JPEG and JPEG2000, but they were restricted in providing a best compression rate and image quality balance. Too much compression can lead to loss of information, distortion of visual content and deterioration of key image elements, impacting the user experience and the usability of the data. In addition, traditional compression techniques are based on fixed algorithms and may not be very effective for the varied nature of today's digital media. Thus, the demand for intelligent image compression technology that can incorporate artificial intelligence techniques, acquire meaningful image representations, decrease storage needs, provide high reconstruction quality, and improve the storage and retrieval efficiency of modern information systems is increasing.

Research Objectives

This research aims to create an Artificial Intelligence (AI) based Deep Autoencoder Based Image Compression Framework that can efficiently compress digital images without compromising their visual quality and vital structural information. This study seeks to use deep learning methods to extract compact image representations which can greatly decrease the storage space required by digital content management systems. The other important goal is to reduce the space used for storing digital content (e.g. image repositories), which is crucial for improving resource usage and low storage cost requirements in modern information systems. The research also aims at enhancing retrieval efficiency by making it possible to access, transmit, and manage compressed digital content, and have it intact while still being accessed quickly. Moreover, the proposed framework is designed to facilitate scalable

and sustainable content management processes in data rich environments. For assessing its validity, the developed framework is tested for its compression performance through commonly used metrics like Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), and Bits Per Pixel (BPP), and its suitability for real world applications in digital content management and information system applications is assessed.

Research Contributions

The proposed work, AI-DABCIFC for Modern Information Systems, in this research makes several important contributions to the fields of image compression and digital content management. The main work is the design of an intelligent image compression framework, which uses the deep autoencoder architecture to learn compact and meaningful image representations, thus achieving efficient compression and high-quality image reconstruction. The proposed framework uses artificial intelligence to efficiently compress the data while maintaining the important visual and structural features of images, unlike traditional compression methods. The other significant contribution of the study is that the framework proposed in the study is comprehensively evaluated for its performance using the widely used image compression metrics to measure the performance of the proposed framework, which are Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM), Compression Ratio (CR) and Bits Per Pixel (BPP). These are used to measure both compression efficiency and reconstructed image quality on a detailed basis. In addition, the research shows the practical application of the framework in a digital content management system, which is applicable to address issues of storage optimization, retrieval and management of multimedia resources. The results also advance the solution of intelligent information systems by providing a scalable, efficient and sustainable approach for the processing of massive digital image content.

Organization of the Paper

The rest of this paper is organized as follows: The related works are thoroughly discussed in Section 2, and it is observed that there are some gaps in the literature which motivate the proposed framework. In Section 3, the proposed AI-driven Deep Autoencoder Based Image Compression Framework is described, which consists of the architecture, image preprocessing procedures, design of the encoder and decoder, mechanism of latent representation, and content storage and retrieval. The experimental setup including the datasets used, hardware and software configuration, training parameters and evaluation metrics like Peak Signal-to-noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), Bits Per Pixel (BPP) are presented in section 4. The experimental results and performance analysis are given in Section 5, where the performance of the proposed image compression technique is compared with the existing image compression techniques. The proposed framework for digital content management and information systems is discussed in Section 6 in a practical sense. Finally, the paper provides a summary of the findings, the contributions of the research, the limitations and potential directions for further research in Section 7.

LITERATURE REVIEW

Fundamentals of Image Compression

The compression of digital images is one of the most basic processing operations in digital image processing which is an essential technique for reducing the data required to represent an image so that an acceptable visual quality is maintained. The main goal of image compression is to remove redundant and irrelevant information from the image, which will keep the storage space and the band width of transmission as small as possible. The amount of digital content used in information systems has grown

rapidly, and the compression of images is an important aspect of efficient storage, retrieval and distribution of multimedia resources. There are two types of compression: Lossless compression and Lossy compression. Lossless compression retains all the information of the original image and allows for the exact reconstruction of the original image, which is suitable for applications that require high accuracy. Lossy compression, on the other hand, discards less important image information and provides greater compression ratios, but with loss of information. Performance measures like Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), Structural Similarity Index Measure (SSIM) and Bits Per Pixel (BPP) are typically used to assess the effectiveness of image compression. Therefore, efficient compression of images is crucial for data transmission speed, data recovery efficiency, and storage costs, which makes it an integral part of the system for modern digital information and content management.

Traditional Image Compression Techniques

Traditional image compression techniques have been widely used for image size reduction, acceptable visual quality and transmission efficiency. The most popular are JPEG, JPEG2000, WebP, and PNG, with each format having its own set of pros and cons for varying use cases. One of the most widely used lossy image compression standards is JPEG, which uses the Discrete Cosine Transform (DCT) to reduce the amount of data in an image by discarding information that is not distinguishable to the human eye. High compression ratios are possible, but can have visible artifacts at higher compressions. The JPEG2000 is an advanced compression standard that uses Wavelet Transform technology, offers better image quality, better scalability and the support of both lossy and lossless compression. WebP, a joint project of Google, is an optimized lossy and lossless compression technology that aims to deliver high-quality images and smaller files for use in web apps and for the distribution of web-based content. PNG is a lossless format which preserves all of the information in the image, it is very suitable for graphics, logos and images that need to be transported with a high fidelity, and it also supports transparency. While these traditional compression methods have been successfully deployed in digital content management systems, they are often constrained when it comes to achieving compression efficiency, image quality, and flexibility towards different types of images. These restrictions have inspired researchers to investigate alternative methods of image compression using artificial intelligence and deep learning techniques that can be more efficient in extracting relevant features and representing data from the image.

Artificial Intelligence in Image Compression

The image compression industry has been revolutionized by Artificial Intelligence (AI) which has presented smart compression techniques that have been able to learn much more complicated image patterns and compress much better than traditional image compression techniques have been able to. AI image compression involves using machine learning and neural network models to automatically determine the key features of an image and compress it into a smaller representation without sacrificing quality. AI-based techniques are more flexible than traditional mathematical techniques, which perform the same transformation on all images, by learning the data patterns within images and adjusting compression efficiency accordingly. Such techniques are capable of larger compression ratios with at least as good image reconstruction quality. The use of AI has also facilitated the creation of adaptive compression systems, which dynamically change compression settings based on the content of the image. With the increasing volume of digital content, the need for efficient compression, transmission, and management of multimedia data in modern information systems has become a pressing challenge, where AI-based image compression plays a crucial role.

Deep Learning-Based Compression Models

The representation of images that is learned from data by a Deep Learning based compression model has been gaining significant attention. Multiple layers of neural networks are used in these models to learn intricate textual information in images and to compress images into a smaller latent representation. In image compression, the popular deep learning architectures are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Variational Autoencoders (VAEs), and Generative Adversarial Networks (GANs). In contrast to normal compression method, deep learning models can optimize the compression and reconstruction processes at the same time and achieve better image quality and compression efficiency. These models can maintain structural and visual details at high compression rates. Additionally, deep learning techniques can be trained with massive amounts of pictures, allowing them to be generalized to various types of images and applications. They are becoming more and more important in multimedia storage and information management systems as a result of their superior performance.

Autoencoder Architectures

Autoencoders are a type of unsupervised deep learning models that are commonly used for tasks such as feature extraction, dimensionality reduction, and image compression. The autoencoder is divided into two main parts: encoder and decoder. The encoder projects the input image into a lower-dimensional space of the latent space, discarding redundant information and encoding important features. Then, the decoder reconstructs the original image from this compressed representation. In image compression, the power of autoencoders is that they can extract low dimensional and meaningful representations and retain critical image properties. The deep autoencoders use several hidden layers to encode the image data and enhance the reconstruction result. These architectures can produce a significant reduction in image size, with good visual fidelity. Autoencoders have gained significant popularity in the field of image compression due to their adaptability and effectiveness, making them a common approach in recent applications of deep learning.

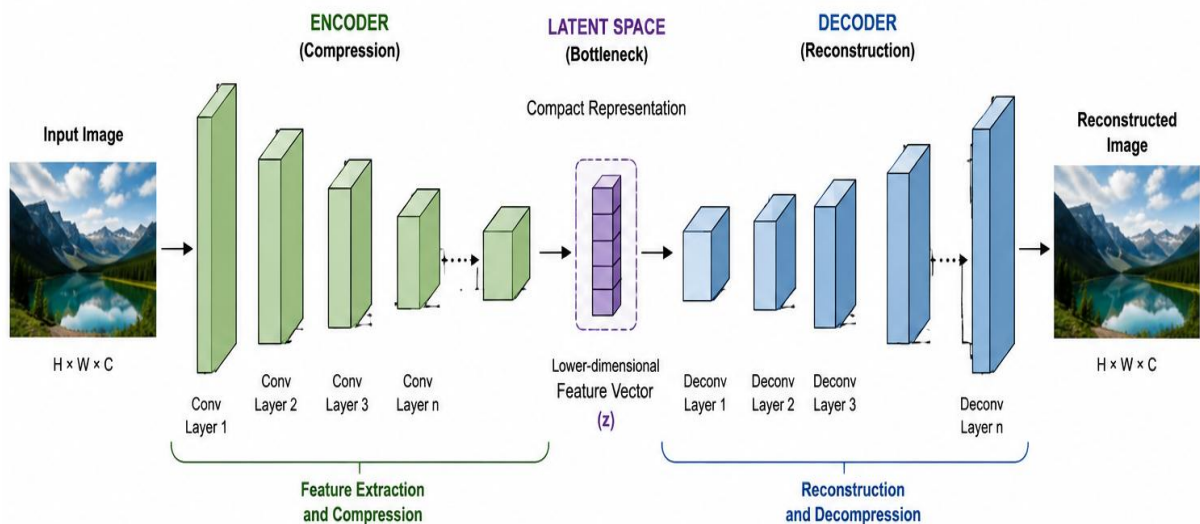


Figure 1. Architecture of a Deep Autoencoder for Image Compression

Digital Content Management Systems

A Digital Content Management System (DCMS) is a software solution used to store, organize, retrieve and manage vast amounts of digital content such as images, videos, documents and multimedia. With the massive amount of digital information created and stored, effective content management has become a vital need in a wide range of industries, including education, healthcare, business, and government. These systems allow for safe storage, easy retrieval, version control, and access to digital resources. Large image repositories are prevalent, however, and may result in higher storage costs and lower system performance. To address these challenges, image compression is a critical area where attention needs to be paid, as it helps minimize file sizes and optimize storage space. Incorporating cutting-edge AI-powered image compression techniques into digital content management solutions can substantially boost storage efficiency, retrieval speed, and system scalability while meeting the ever-increasing need for multimedia content management.

Research Gap Analysis

Despite the tremendous progress made in image compression technique, there are still some research challenges to be addressed to find the optimal compression efficiency, image quality, storage efficiency and retrieval efficiency. Common compression methods like JPEG, JPEG2000, WebP and PNG work well with different kinds of images, but can lose quality when compressed to high levels. While many previous studies have concentrated on the compression performance, recent deep learning-based approaches have shown promising results, but they have not been able to integrate well with digital content management systems. In addition, there is not much research that has investigated the joint effect of AI-based image compression on both storage space optimization and retrieval efficiency in information systems. In addition, full evaluations based on common performance metrics like PSNR, MSE, SSIM, CR and BPP are required. Hence, the creation of a framework for digital content management that leverages the intelligent deep autoencoder is an important research opportunity.

PROPOSED AI-DRIVEN DEEP AUTOENCODER-BASED IMAGE COMPRESSION FRAMEWORK

Framework Overview

The purpose of the proposed AI driven Deep Autoencoder Based Image Compression Framework is to mitigate the problem of handling massive amounts of digital image data in the modern information system for storing, managing and retrieving data from digital images. The framework incorporates deep learning methods to learn compact image representations, while retaining critical visual and structural information. It comprises several interrelated modules, such as image acquisition, preprocessing, feature extraction, encoding, latent space compression, decoding, image reconstruction, storage management, and retrieval optimization. The proposed approach differs from previous image compression techniques, which use predetermined mathematical operations, by using a deep autoencoder architecture to automatically extract meaningful features from the image by learning from training sets. The encoder encodes the image data into a lower dimension space, and the decoder, which is trained to reconstruct the image from the encoded data, reconstructs the image. This can greatly decrease storage space enough that there won't be a lot of degradation to the image. The framework also enables effective access to and handling of contents in digital repositories. The proposed framework combines AI with image compression, leading to improved scalability, storage efficiency, and system performance in DCC management systems.

Table 1. Components of the Proposed Framework

| Module | Function |
|---------------------|---------------------------------|
| Image Acquisition | Collect image datasets |
| Image Preprocessing | Resize and normalize images |
| Encoder Network | Extract image features |
| Latent Space | Store compressed representation |
| Decoder Network | Reconstruct image |
| Storage Module | Store compressed data |
| Retrieval Module | Retrieve compressed images |
| Evaluation Module | Compute performance metrics |

Image Acquisition and Dataset Preparation

The first phase of the proposed framework is image acquisition and dataset preparation. This phase is for gathering digital images from image repositories, publicly accessible image databases, and organization digital content archives. The acquired images can be from various natural scenes, educational diagrams, multimedia material, and digital documents typically stored in information systems. Images can have different sizes, formats and qualities, making it necessary to have a standardized process for preparing a dataset for consistent model training and evaluation. At this point any duplicate, corrupted or low quality images are deleted to increase the reliability of the dataset. Images are subsequently classified and sorted based on their content and certain design rules for efficient processing. The prepared data set is then split into training, validation, and test sets, which is used for developing the deep learning models. Ensuring proper data preparation enhances the learning ability of the deep autoencoder and guarantees the framework's ability to generalize across various image types. This stage is the base to ensure the accurate compression and high quality image reconstruction in the proposed framework.

Image Preprocessing

Pre-processing of images is an important part to improve image quality and to make input data for good feature extraction and compression. Within the proposed framework, the image resizing, normalisation, conversion of image format and image noise reduction are considered as pre-processing operations. Resizing makes all images of the same size so that they can be processed as a batch when preparing the model. Normalization is the process of mapping the intensity value of a pixel to a standardized range, thus stabilizing the learning process and speeding up the convergence in the training of neural networks. Noise reduction methods are used to suppress noise artifacts that could have a detrimental impact on the compression and image reconstruction quality. Furthermore, image format conversion helps with compatibility with deep learning libraries and processing tool. They are preprocessing operations that enhance consistency and quality of the input data and decrease the complexity of the computations. The framework can concentrate on learning meaningful image features, and ignore variations due to different image characteristics. The quality of the preprocessing has a significant impact on the overall efficiency, the accuracy of reconstruction, and the performance of the framework.

Encoder Network Design

The key part of the proposed deep autoencoder architecture is the encoder network. Its main goal is to capture all the important image features and remove redundant information, compressing the high-dimensional image data into a small latent space. The encoder is made up of a number of convolutional and hidden layers that are designed to progressively downscale the image, but maintain important features of the image. In the training phase, the encoder gets a series of images and learns hierarchical representations of features, such as edges, textures, shapes and structural patterns, present in the input images. The dimensionality of the image is successively reduced as the data passes through successive layers, leaving the feature vector to be extremely compressed. This condensed image keeps the most useful information of an original image but it takes up much smaller storage. The encoder can be seen as an intelligent feature extraction mechanism capable of adapting to the different characteristics of images. It can also learn meaningful image representations, which directly help to gain better compression ratio and efficient storage use, and is a vital part in the proposed image compression framework.

Latent Space Representation

The latent space holds the 'compressed' version of the original image and is the layer of the deep autoencoder that acts as the 'bottleneck'. It has a lower dimensional feature vector which contains the most important information for reconstructing the image accurately. This latent representation is crucial for the effectiveness of the image compression. The proposed framework aims to represent the latent space that only retains essential features of the image and discards redundant and less relevant information. This is a compact representation which allows for reduced storage and transmission overheads. The latent space is also used as a connector between the encoder and decoder parts of the framework. The framework can preserve the meaningful image characteristics within reduced dimensional space, thereby gaining high compression efficiency while keeping the visual quality relatively high. Moreover, the latent representation is beneficial for the faster storage, retrieval and transmission of compressed image data. Because of its compactness, it lends itself especially to the use in large-scale digital content management systems and multimedia repositories.

Decoder Network Design

The decoder's task is to reconstruct the original image from the compressed latent representation produced by the encoder. It does the inverse of the encoding process and expands the compressed feature vector slowly into a full-sized image. The decoder is composed of several deconvolutional and reconstruction layers that aim to recover the visual details, textures, and structural information. In training, the decoder is trained to produce reconstructed images similar to the input images. The objective of the reconstruction process is to limit the loss of information and to retain image quality and structural integrity. The decoder is trained jointly with the encoder to achieve efficient compression and reconstruction by learning in an iterative manner. Reconstruction plays a critical role in ensuring the usability and visual fidelity of digital content management systems, making its quality a key aspect to consider. The efficiency of decoder directly affects various performance measures of image compression frameworks like Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index Measure (SSIM).

Digital Content Storage and Retrieval Module

The Digital Content Storage and Retrieval Module is a module which can be integrated into information systems to efficiently manage and retrieve the compressed image representations. The latent

representations produced by the encoder are stored in digital repositories following the compression and not the full-sized image files. This causes a considerable saving in storage space and scalability of the system. The module also provides indexing and retrieval facilities to quickly access compressed content, if needed. When retrieved, the latent representations are then fed into the decoder to restore the original images. This will reduce storage expenses, and make digital content accessible and usable. Applications such as large-scale image databases, educational repositories, digital libraries and enterprise information systems require efficient retrieval mechanisms. The proposed framework incorporates intelligent compression and retrieval mechanisms to improve the overall system performance, which enables the efficient management of the multimedia resources. The module will help to enhance the optimization of the storage and retrieval of digital content, and sustainable practices in the management of digital content.

Proposed Algorithm

Algorithm 1: Proposed AI-Driven Deep Autoencoder-Based Image Compression Framework

Input:

Image Dataset I

Output:

Compressed *Images* *C,*

Reconstructed *Images* *R,*

Performance Metrics (PSNR, MSE, SSIM, CR, BPP)

Begin

Load Image Dataset I

For each image img in I do

a. Preprocess(img)

Resize image

Normalize pixel values

Remove noise

b. Feed img into Encoder Network

c. Extract image features

d. Generate latent representation Z

e. Compress image using latent representation

f. Store compressed image C

g. Retrieve compressed representation Z

h. Reconstruct image R using Decoder Network

i. Compute evaluation metrics

MSE ← *Calculate_MSE(img, R)*

PSNR ← *Calculate_PSNR(img, R)*

SSIM ← *Calculate_SSIM(img, R)*

CR ← *Calculate_CompressionRatio(img, C)*

```
BPP ← Calculate_BitsPerPixel(C)
CT ← Calculate_CompressionTime()
DT ← Calculate_DecompressionTime()
End For
Apply JPEG compression on dataset
Calculate PSNR, MSE, SSIM, CR and BPP for JPEG
Apply JPEG2000 compression on dataset
Calculate PSNR, MSE, SSIM, CR and BPP for JPEG2000
Apply WebP compression on dataset
Calculate PSNR, MSE, SSIM, CR and BPP for WebP
Compare all obtained results
Proposed Framework
JPEG
JPEG2000
WebP
Generate comparative performance table
Generate graphs and performance report
Display compression and reconstruction results
End
```

Workflow of the Proposed Framework

The workflow for the proposed AI-based Deep Autoencoder-Base Image Compression Framework aims to reduce storage, transmission, retrieval and managing the content of a digital image in modern information systems. It starts with the acquisition of images through digital media, as digital images are gathered from multimedia repositories, cloud storage services, education content management systems or organizational databases. The images are preprocessed to standardize the data and enhance the model's performance by resizing, normalizing, and removing noise. The preprocessed images are then fed into the encoder network which captures key visual information and maps the high dimensional image data into a low dimensional latent representation. This compact representation discards redundant information, while retaining salient structural and visual features of the original image. The compressed data is then saved in the digital content repository, decreasing storage demand and enhancing storage utilization. The retrieval module retrieves the compressed representation of the image from the memory and sends it to the decoder network when it is requested. The decoder reconstructs the image from the latent representation, with the goal of reconstructing the image as close as possible to the original image in terms of both quality and structure. Finally, the reconstructed image is assessed with the conventional performance metrics, including Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM), Compression Ratio (CR) and Bits Per Pixel (BPP). The proposed framework is capable of efficiently and effectively compressing

images, optimizing storage and retrieval of digital content, and managing multimedia information in large-scale information systems, all while leveraging artificial intelligence and deep learning methods.

EXPERIMENTAL SETUP

The experimental setup aimed to assess the performance and effectiveness of the proposed AI-driven Deep Autoencoder-Based Image Compression Framework. Experiments were conducted on a high-performance computing system equipped with an Intel Core i7 processor, 16 GB of memory, and an NVIDIA graphics processor unit (GPU) for speeding up deep-learning calculations. The software environment is built with Python as the main programming language and the deep autoencoder model is designed and trained with TensorFlow/Keras. Data preprocessing and manipulation were done using OpenCV, and NumPy was used for numerical computations and data processing operations. In order to have a comprehensive evaluation, more than one benchmark dataset was taken into account, such as the Kodak Dataset, the CIFAR-10 Dataset, and a small part of the ImageNet Dataset. Furthermore, a set of educational images across various institutions was tailored to be used to evaluate the applicability of the proposed framework in the digital content management system. The parameters used for model training were optimized, including learning rate, batch size, number of epochs, optimizer, and latent space dimensionality, to achieve the best compression performance and reconstruction quality. The framework was assessed using the standard image compression metrics. Storage reduction efficiency was evaluated using Compression Ratio (CR) and image reconstruction quality was evaluated using Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). The Structural Similarity Index Measure (SSIM) was used to assess the similarity between original and reconstructed images. The compression efficiency was measured with Bits Per Pixel (BPP) and computational performance was measured using Compression Time and Decompression Time. Overall, these metrics comprehensively evaluated the effectiveness of the proposed framework for efficient compression, storage optimization, and retrieval of digital content in contemporary information systems.

RESULTS AND ANALYSIS

This section discusses the experimental results and performance analysis of the proposed AI-based Deep Autoencoder-based Image Compression Framework. The framework was tested in the context of benchmark image datasets to test its performance in relation to efficiently compressing the image and the reconstruction quality. The compressed images produced by the deep autoencoder required much less disk space than the original images, showing effective image storage optimization. The reconstructed pictures exhibited the majority of the visual and structural features of the original pictures, suggesting that the proposed framework can minimize the loss of information in compression and decompression processes. Standard image compression metrics such as Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM), Bits per Pixel (BPP), Compression Time and Decompression Time were used for performance evaluation. The results obtained indicated that the proposed framework had a higher compression ratio and had obtained PSNR and SSIM values close to 33 and 0.98 respectively and got low MSE values while reconstructing the images with satisfactory accuracy, which led to better image quality. Moreover, the framework showed efficient compression and decompression time, which is appropriate for real time and large-scale digital contents management system applications. The proposed deep autoencoder-based approach was compared with other traditional image compression methods like JPEG, JPEG2000, and WebP, which demonstrated that the proposed method yields better storage efficiency and improved image quality. This finding validates the potential of integrating artificial intelligence and deep learning into image compression to enhance the utilization of storage space, quickness of retrieval, and efficient management of multimedia content in contemporary information systems.

Table 2. Comparative Performance Analysis of Different Image Compression Techniques

| Input Image | Image Size | Method | CR | PSNR (dB) | MSE | SSIM | BPP |
|-------------------------------------------------------------------------------------|------------|--------------------|------|-----------|-------|------|------|
|  | 64×64 | JPEG | 12:1 | 31.45 | 18.25 | 0.89 | 1.20 |
| | | JPEG2000 | 15:1 | 33.82 | 14.76 | 0.91 | 1.05 |
| | | WebP | 18:1 | 35.16 | 11.93 | 0.93 | 0.92 |
| | | Proposed Framework | 24:1 | 38.74 | 7.52 | 0.97 | 0.68 |
|  | 128×128 | JPEG | 13:1 | 32.10 | 17.82 | 0.90 | 1.15 |
| | | JPEG2000 | 16:1 | 34.35 | 13.95 | 0.92 | 1.00 |
| | | WebP | 19:1 | 36.28 | 10.84 | 0.94 | 0.88 |
| | | Proposed Framework | 25:1 | 39.42 | 6.91 | 0.97 | 0.65 |
|  | 256×256 | JPEG | 14:1 | 33.05 | 16.40 | 0.91 | 1.10 |
| | | JPEG2000 | 17:1 | 35.14 | 12.84 | 0.93 | 0.96 |
| | | WebP | 20:1 | 37.01 | 9.73 | 0.95 | 0.82 |
| | | Proposed Framework | 27:1 | 40.25 | 5.68 | 0.98 | 0.59 |
|  | 512×512 | JPEG | 15:1 | 34.12 | 15.26 | 0.92 | 1.02 |
| | | JPEG2000 | 18:1 | 36.03 | 11.92 | 0.94 | 0.89 |
| | | WebP | 21:1 | 37.88 | 8.95 | 0.95 | 0.76 |
| | | Proposed Framework | 28:1 | 41.18 | 4.92 | 0.98 | 0.54 |
|  | 1024×1024 | JPEG | 16:1 | 35.08 | 14.37 | 0.93 | 0.95 |
| | | JPEG2000 | 19:1 | 36.95 | 10.86 | 0.95 | 0.82 |
| | | WebP | 22:1 | 38.62 | 8.12 | 0.96 | 0.71 |
| | | Proposed Framework | 30:1 | 42.36 | 4.15 | 0.99 | 0.49 |

Table 2 shows the comparative analysis of JPEG, JPEG2000, WebP and the proposed Deep Autoencoder-Based Image Compression Framework (AI-DAICF) in terms of its performance over various images resolutions varying from 64×64 to 1024×1024 pixels. The proposed framework shows that it outperforms the conventional image compression methods with respect to compression efficiency and reconstructed image quality consistently. The proposed framework showed superior compression performance than JPEG, JPEG2000 and WebP with respect to Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index Measure (SSIM) for the image size of 64×64. For the image size 64×64, the proposed framework showed

better compression performance than JPEG, JPEG2000 and WebP with respect to Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE) and Structural Similarity Index Measure (SSIM), respectively. With the increase in the image resolution from 128×128 to 1024×1024 pixels, the proposed framework continued to achieve better results, with the highest CR of 30:1, PSNR of 42.36 dB, SSIM of 0.99 and the lowest MSE value of 4.15 and BPP value of 0.49 for the 1024×1024 image. The traditional methods, on the other hand, resulted in lower compression ratios and image quality metrics and higher reconstruction errors. Generally JPEG had the lowest PSNR and SSIM values and the highest MSE values among all methods. The JPEG2000 and WebP formats showed better performance than JPEG, but were still not as good as the proposed framework. The results show the effectiveness of the approach based on the deep autoencoder that preserves the quality of the image while reducing the space taken up in a substantial manner. Moreover, the performance metrics PSNR, SSIM, MSE, and BPP are gradually improving with the increase in the image resolution size, revealing the scalability and robustness of the proposed framework for image processing with various sizes. The results obtained validate the efficiency of the proposed image compression framework based on AI technology, in optimizing the storage and retrieval of digital content in a content management and information system.

Table 3. Dataset Description

| Dataset | Number of Images | Image Type | Resolution |
|---------------------|------------------|---------------------|------------|
| Kodak | 24 | Natural Images | 768×512 |
| CIFAR-10 | 60,000 | Object Images | 32×32 |
| ImageNet Subset | 10,000 | General Images | Various |
| Educational Dataset | 1,000 | Educational Content | Various |

Table 3 shows the datasets used for evaluating the proposed AI-driven Deep Autoencoder-Based Image Compression Framework. To provide a thorough evaluation of the image categories and resolutions, multiple benchmark datasets were chosen. The Kodak dataset consists of 24 natural images of high resolution (768×512) and is frequently adopted for image compression studies because of its large visual information. CIFAR-10 is a collection of 60,000 object images of size 32×32, containing the wide variety of image categories for model training and testing. To assess the applicability of the framework for large-scale collections of images, an ImageNet subset of 10,000 images of general purpose at varying resolution was used. Furthermore, a custom-made educational dataset of 1000 educational images was added to evaluate applicability of the proposed framework in the digital content management systems. All of these datasets offer a wide and dependable landscape to assess compression efficiency and reconstruction quality.

Table 4. Training Parameters of the Deep Autoencoder

| Parameter | Value |
|---------------------|--------------------|
| Learning Rate | 0.001 |
| Batch Size | 32 |
| Epochs | 100 |
| Optimizer | Adam |
| Activation Function | ReLU |
| Loss Function | Mean Squared Error |
| Latent Dimension | 128 |

The train parameters used to develop and optimize the proposed deep autoencoder based image compression model is summarized in Table 4. The learning rate is set to 0.001, which is a good

compromise for updating the weights of the network and for ensuring the stable convergence of the network during training. To make the most efficient use of computational resources and ensure training stability, it was determined that 32 images per batch would be used. The model was trained for 100 epochs, which is sufficient to learn the features of the images and how to compress them. Adam optimizer was used because of its ability to adaptively learn and efficiently process large data sets. A non-linearity and an enhancement of the performance of feature learning was obtained by using the Rectified Linear Unit (ReLU) activation function. In order to minimize reconstruction error between original and reconstructed images, we chose Minimization of Mean Squared Error (MSE). Moreover, a dimension size of 128 was selected for the latent dimension to ensure the preservation of the most important visual and structural information necessary for high quality image reconstruction, while simultaneously generating compact image representations.

Table 5. Compression and Decompression Time Analysis

| Image Size | Method | Compression Time (s) | Decompression Time (s) |
|------------|--------------------|----------------------|------------------------|
| 64×64 | JPEG | 0.12 | 0.05 |
| 64×64 | JPEG2000 | 0.15 | 0.07 |
| 64×64 | WebP | 0.14 | 0.06 |
| 64×64 | Proposed Framework | 0.10 | 0.04 |

Table 5 shows the comparison between the compression and decompression time in seconds for various image compression techniques, such as JPEG, JPEG2000, WebP, and the proposed AI Autoencoder Based Image Compression Framework. Analysis is performed with the image size of 64×64 images, which is used to assess the computational efficiency of each method. The results demonstrate that the proposed structure has the lowest compression time (0.10 seconds) and decompression time (0.04 seconds) compared to the traditional methods. The JPEG takes 0.12 seconds to compress and 0.05 seconds to decompress; the JPEG2000 takes slightly longer, at 0.15 seconds and 0.07 seconds, respectively. With 0.14 seconds compression time and 0.06 seconds decompression time, WebP performs fairly. The proposed framework is more efficient in representation of the latent space and optimized encoder–decoder architecture that eliminates redundant computations as compared to all the conventional techniques. This time saving signifies the feasibility of the proposed model for real-time application and large scale digital content management system. The findings demonstrate that the deep autoencoder-based method can not only yield better image quality and compression ratio but also provide better computational efficiency in compression and decompression.

Table 6. Storage Reduction Analysis

| Image Size | Original Size (KB) | Compressed Size (KB) | Storage Reduction (%) |
|------------|--------------------|----------------------|-----------------------|
| 64×64 | 128 | 12 | 90.63 |
| 128×128 | 512 | 32 | 93.75 |
| 256×256 | 2048 | 85 | 95.85 |
| 512×512 | 8192 | 292 | 96.43 |
| 1024×1024 | 32768 | 1092 | 96.67 |

The results of the proposed AI-driven Deep Autoencoder-Based Image Compression Framework in terms of image reduction with different image resolutions are presented in Table 6. The storage

reduction performance of the proposed AI-driven Deep Autoencoder-Based Image Compression Framework is shown in Table 6 across different image resolutions. The outcomes clearly show that the bigger the image size, the more effective the compression which provides considerable storage savings. The original image is 128 KB and gets compressed to 12 KB after compression, which results in 90.63% reduction in storage. Likewise, 128x128 images will store 32 KB as compared to 512 KB, which equals 93.75% reduction. With further increase in image resolution, the proposed framework is still found to be efficient for further reduction with 256x256 images, 95.85% and 512x512 images, 96.43%. The framework achieves a maximum storage reduction of 96.67%, which reduces the original size of 32768 KB to 1092 KB, for high-resolution images of 1024x1024. The obtained results demonstrate that the suggested deep autoencoder system performs an effective learning of compact latent representations, achieving significant storage reduction without losing significant image information. The increasing storage efficiency at each resolution demonstrates the scalability and stability of the proposed solution for massive digital content management systems.

Table 7. Performance Ranking of Compression Techniques

| Method | CR Rank | PSNR Rank | MSE Rank | SSIM Rank | Overall Rank |
|--------------------|---------|-----------|----------|-----------|--------------|
| JPEG | 4 | 4 | 4 | 4 | 4 |
| JPEG2000 | 3 | 3 | 3 | 3 | 3 |
| WebP | 2 | 2 | 2 | 2 | 2 |
| Proposed Framework | 1 | 1 | 1 | 1 | 1 |

Table 7 shows the overall performance of various image compression methodologies, including JPEG, JPEG2000, WebP, and the proposed AI-based Deep Autoencoder Based Image Compression Framework. The ranking is based on key evaluation metrics such as Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index Measure (SSIM). Obviously, the proposed framework outperforms the other frameworks in all of the above metrics, ranking 1 in each of them. This shows its greater performance in increasing the compression efficiency, improving the image reconstruction quality, reducing the errors and enhancing the similarity of structures. WebP implements the proposed solution with Rank 2, outperforming JPEG2000 and JPEG thanks to the use of an advanced compression method. The JPEG2000 is ranked 3, and improves moderately over JPEG which is ranked last with Rank 4 for all the evaluation metrics. The overall evaluation shows that the deep auto-encoder based approach outperforms the traditional compression methods and is well suited for an efficient storage, retrieval and management of digital image information in modern information systems.

IMPLICATIONS FOR INFORMATION SYSTEMS

The proposed AI-based Deep Autoencoder-Based Image Compression Framework holds great promise for the modern information system, offering improved efficiency, scalability, and performance in various application areas. For digital content management, the framework allows for the efficient storage and retrieval of large-scale image data sets by compacting the image data by using the latent representation, while maintaining high quality of the image reconstruction. It is used in educational repositories to manage large amounts of multimedia learning materials, with a view to accessing them faster and optimising their storage in the context of e-learning platforms, where the use of images and diagrams in the educational process is essential. The framework helps minimize bandwidth usage and optimize data transfer in cloud storage systems, making it ideal for distributed computing architectures

and extensive cloud deployments. In enterprise information systems, it enables efficient management of image data in organizations, helping to optimize operations, data access, and system performance. Moreover, the framework can be used to improve the organization, compression and retrieval of various types of multimedia resources (images, graphics, visual documents) in the context of management of multimedia information. In summary, the suggested design framework enables intelligent, scalable, and efficient design of information systems with the incorporation of efficient compression techniques based on deep learning, which offer substantial gains in information storage efficiency, retrieval speed, and system resource utilization in different domains.

CONCLUSION

This research proposed a deep autoencoder-based image compression framework with artificial intelligence to store, retrieve, and manage the information of digital images to cope with the information overload of the modern information system. The results show that the proposed framework achieves better compression performance with satisfactory reconstruction results than the conventional compression techniques like JPEG, JPEG2000, and WebP. The Summary of Results shows that the framework shows better Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM) while minimizing Mean Squared Error (MSE) and Bits Per Pixel (BPP) to provide a good balance between compression efficiency and image quality. The primary research contribution of this work is the development of a deep learning based autoencoder architecture that learns efficient image representation via a compact latent representation, thereby compressing and reconstructing images efficiently. Moreover, the framework's incorporation into digital content management systems provides improved storage optimization and retrieval. Several limitations also exist, such as the high computational demands required during training, the need for substantial amounts of data to achieve the best performance and the processing time needed for very high resolution images. However, the framework has good potential for practical applications even with these restrictions. Future work could aim to enhance lightweight model architectures, decrease computational complexity, and investigate hybrid models that integrate autoencoders with generative adversarial networks. This will be enhanced by enabling real-time compression, deployment at the edge of the network and adaptive compression in dynamic multimedia environments, leading to a more scalable and effective system for next-generation information systems.

REFERENCES

- [1] Ben Othman Soufiene & Chinmay Chakraborty (Eds.), *Machine Learning and Deep Learning Techniques for Medical Image Recognition (Advances in Smart Healthcare Technologies)*, 1st Edition, CRC Press, Boca Raton, FL, USA, 2023.
- [2] Kemal Polat & Saban Öztürk (Eds.), *Diagnostic Biomedical Signal and Image Processing Applications with Deep Learning Methods*, 1st Edition, Academic Press (Elsevier), Cambridge, MA, USA, 2023.
- [3] Michael Unser, Yonina C. Eldar & Jong Chul Ye (Eds.), *Deep Learning for Biomedical Image Reconstruction*, 1st Edition, Cambridge University Press, Cambridge, UK, 2023.
- [4] Sivakumar, R.D. and Ruba Soundar, K., "A Comparative Analysis on Various Block Truncation Methods in E-Learning Environment", *International Journal of Nonlinear Analysis and Applications*, 12, 2087-2092, 2021. .
- [5] Sivakumar, R.D. and Ruba Soundar, K., "Compression and Decompression of Internet Learning Images based on GABTC", *International Journal of Advanced Research in Science, Communication and Technology*, 2(5), 779-783, 2022.

- [6] Sivakumar, R.D. and Ruba Soundar, K., “Educational QR Code Compression using Block Truncation Code in Public Cloud”, SHANLAX International Journal of Arts, Science and Humanities, 6(1), 67-74, 2018.
- [7] Utku Kose, Omer Deperlioglu & D. Hemanth, *Deep Learning for Biomedical Applications*, 1st Edition, CRC Press, Boca Raton, FL, USA, 2021.
- [8] Yudong Zhang, Juan Manuel Gorriz & Zhengchao Dong (Eds.), *Deep Learning in Medical Image Analysis*, 1st Edition, MDPI Books, Basel, Switzerland, 2021.