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Machine Learning Based Image Compression by Reducing Dimensionality

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Abstract
As medical imaging technologies continue to proliferate and generate massive amounts of data, data compression has become increasingly important for their storage, transit, and processing in the modern world. In telemedicine practices, it is common for medical images to be sent from one site to another. It is now important to minimize image size while maintaining diagnostic information in order to transmit and keep these high-quality images. Medical images compression is a technique that helps save money on transfer and storage by advising on the use of lossy and lossless compression algorithms. Medical images compression calls for a machine learning and IOT infrastructure. Multistage PCA, the Discrete Anamorphic Stretch Transform, and PCA using the Johnson-Lindenstrauss Lemma algorithm are just a few examples of dimensionality reduction techniques used in image compression.We provide many options for decreasing the dimensionality of image data. Among these techniques are PCA using the Johnson-Lindenstrauss Lemma algorithm, Discrete Anamorphic Stretch Transform, and Multistage Principal Component Analysis. The research suggests that combining PCA based on the Johnson-Lindenstrauss lemma with Shannon-Fano coding can lead to significant compression gains.

Keywords: Image Compression, Machine Learning, IoT, CT, MRI, PCA

Introduction
The methods and models used to analyze multimedia data have come a long way in recent years. These enhancements have taken many approaches, such as more accurate depiction and interpretation. It is a technological development that new ways have been developed to compress multimedia data. These algorithms find special value in a number of data storage systems for multimedia information and other applications. The compression process is another name for data reduction. In computing, data presentation size may be decreased using a process known as compression. When discussing data, the phrase "compression" may refer to a variety of processes, including source coding, data Compression, bandwidth compression, and signal compression. It's possible that a signal may be anything from an image to a video to a piece of music. However, medical imagery is what this study is primarily concerned with.

By eliminating unnecessary information about the picture's spatial and color relationships, image compression may lower the number of bits needed to describe the image. Dimension Reduction, also known as Dimensionality Reduction, is a technique used in statistics to cut down on the number of potential independent variables. This technique may be broken down even further into "feature selection" and "feature extraction." Dimensionality reduction approaches, such as Multistage Principal Component Analysis (PCA), Discrete Anamorphic Stretch Transform (DAST), and PCA based on Johnson- Lindenstrauss Lemma (JL-PCA), are discussed in this paper for their application to picture compression of varying image types and resolutions. In this paper, we'll look into how various Dimensionality reduction methods may be used to produce compression. Compression ratio (CR), compression time (CT), and decompression time (DT) are some of the metrics used to evaluate the various methods. Other metrics include peak signal-to-noise ratio (PSNR), mean squared error (MSE), mean absolute error (MAE), and compression ratio (CR).

Literature on Redundancy Allocation

As medical imaging becomes more commonplace in clinical practice, and as the data quantities produced by different medical imaging modalities continue to grow, the need to compress medical images becomes more pressing. Digital medical images data sets must be compressed prior to dissemination, storage, and administration. Over the course of the previous several decades, many proposals for image compression standards have been made by international standardization groups. Medical images compression approaches have already been evaluated using machine learning and IoT [1-9]. With a focus on more recent standards that were overlooked, this paper covers the present status of image compression standards in medical imaging applications and tackles certain legal and regulatory issues around the use of compression in medical settings using machine learning and IoT framework.

Medical imaging has advanced to the point that it is now a crucial tool in the diagnosis of health issues in humans. Numerous surgical procedures are being postponed, hospital beds are being utilized more effectively, and patient outcomes are being enhanced as a result of medical imaging research [1,2]. From the beginning of PACS, it was understood that medical Images would need to be compressed in some way, and novel compression methods were proposed even before standardized compression procedures were available [3]. Adopting digital communication standards is necessary due to the high cost and time commitment associated with using proprietary compression methods when moving data across systems using IoT [4]. It would be hard to present a comprehensive discussion of all medical imaging procedures here due to the breadth and depth of the area of medical imaging.

As a result, we will zero attention on the most popular types of medical imaging and discuss the basic features of their data compression [5]. A single projection plane is used to depict anatomical features in X-ray radiography, and this plane is subsequently projected onto a detector plane. Instead, computed tomography (CT) imaging uses several projections taken at various angles to create a 3D volume of the anatomical feature of interest [6]. Magnetic resonance imaging (MRI) is a subset of imaging technology that makes use of nuclear magnetic resonance as its foundation [7]. Image contrast in magnetic resonance imaging (MRI) is affected by a variety of tissue-specific parameters and imaging-specific acquisition settings. Changing the MRI's parameters can produce images with drastically different contrast. Because of the far greater variety of contrasts acquired during a typical test, the amount of data generated by MRI scans is substantially more than that generated by CT files, even though MRI images are often obtained at lower spatial resolution.

Rician distributions may be used to describe thermal noise in MRI, both from the receiver coil and the sample [8]. Some of the most well-known earlier approaches of compressing medical images have been investigated using machine learning and IoT, as is evident from the literature. Medical image compression has been the subject of extensive study, however only a few numbers of methods are practical in practice due to compression being applied to the whole image without knowing which part is most important from a diagnostic standpoint and the current method of picture compression does not guarantee a high enough perceived quality at the appropriate bit rate. To solve these issues, this paper provides a suitable machine learning and IoT framework.

Methodology

The paper discusses the issue of translating tumor images across various modalities, as shown by the supplied data. The dataset offered consists of unpaired volumes of magnetic resonance (MR) and computed tomography (CT) imaging data from a total of 20 individuals. The dataset has a total of 179 axial magnetic resonance (MR) and computed tomography (CT) images in two-dimensional (2D) format. The dataset was obtained within the time frame spanning from April 2016 to December 2019. The dataset comprises CT and MR image volumes acquired specifically for the purpose of radiation treatment planning for malignancies. In this paper, we use the multi-stage technique to divide the training set into k groups, then conduct principal component analysis to each group separately. In a clustering technique, the mean squared error (MSE) can serve as an objective function for extracting main components. When the size of the clusters exceeds a certain threshold, an adaptive number of eigenvectors can be calculated.

The number of eigenvectors in a cluster must also be kept small. These parts can then be used for picture encoding and decoding. Cluster analysis seeks to group data points into meaningful categories so as to facilitate issue solving. To be more precise, the training data is partitioned into k clusters, each of which has n examples that are comparable to those in other clusters and can be monitored using IoT framework. In this case, we use a multi-stage approach to improve the quality of the rebuilt image. To further enhance the recovered effect of certain clusters with complicated structures, Multi-stage PCA would increase the number of principal components and eliminate redundant recorded variables for clusters with better retrieved effects. In other words, the visual impact of pictures would change very little (for clusters with poor recovered quality) if the retrieved image quality was improved.

As a method of progressive categorization, multi-stage clustering may efficiently prune superfluous information and boost the number of main components to enhance the recovered effect of specific clusters with intricate structures. In order to simulate the effects of diffraction of an image via a physical material with a particular nonlinear dispersive feature, the Discrete Anamorphic Stretch Transform was developed. The image may be represented with less data by employing space-bandwidth compression, which maintains the same level of quality. In contrast to Compressive Sensing (CS), which relies on tweaks to the sampling method, this diffraction-based compression is accomplished by a reorganization of the image's arithmetic.

If we think of n and m as discrete spatial variables in two dimensions, we may write the original picture as B[n, m]. Our approach for image compression involves running the picture through a DAST and then down sampling it uniformly at a rate lower than the image's Nyquist rate. The original picture is reconstructed from the compressed one by first up sampling the compressed one and then using inverse DAST. The image is warped by DAST in such a way that the intensity bandwidth is decreased but the overall image size remains the same. As a result, there is less information required to depict the image, and the spatial coherence is improved.

DAST is a method for image compression that involves a spatial warp of the image according to the nonlinear phase profile [n, m]. The DAST Local Frequency (LF) profile is the 2D spatial gradient (derivative) of the DAST Kernel phase function, and it is used to describe the applied warp. In the context of the time domain, low-frequency (LF) is synonymous with the instantaneous frequency in the 2D spatial domain. We provide a mathematical technique to characterize both the bandwidth of the original picture and the spatial size that would result from performing the transformation, which should help in choosing between [n, m] and the DAST Kernel. This application demonstrates both the image compression and the DAST process that led to it.

With the suitable phase profile, an anamorphic transformation may narrow the dynamic range of brightness while simultaneously increasing coherence. In order to resample the final picture at a lower rate without degrading the quality, DAST compresses the brightness bandwidth. We point out that the data overhead for reconstruction is minimal, as only five parameters (actual numbers) are needed. Vector quantization and entropy encoding can be used in conjunction with this approach to further compress the picture data [9]. Additionally, the resample picture might undergo secondary compression using a format like JPEG or JPEG 2000. DAST image compression is used on each individual color channel when applied to color pictures.

Up sampling and propagation via the DAST, that makes use of Measurement of frequency in local environment, make up the decoding process. This may be accomplished through the use of a variety of methods using IoT, including phase discrimination and iterative approaches. These methods of phase discrimination compare the scalar amplitude of the signal in two different forms (filtered and unfiltered). These numbers are used to reconstruct the phase.

Johnson-Lindenstrauss PCA (JL-PCA) Method

The Johnson Lindenstrauss Lemma's objective is to discover a mapping between a point set p in RP and a point set Q in Rk(k>p) [8]. The image processing industry has adopted the Johnson Lindenstrauss Lemma. Given that high-dimensional vectors are used to represent picture characteristics. Compressing the vectors, while maintaining the degree of similarity between any two vectors, is possible thanks to dimension reduction techniques. This paves the way for on-the-ground picture analysis done through machine learning and IoT. The Johnson-Lindenstrauss Lemma, one of the most significant discoveries in dimensionality reduction, states that distances between any two points in a high-dimensional space may be translated to a much lower-dimensional space of k>O (log m) without being distorted by more than a factor of (1 +/- s). The projection of the high-dimensional points onto k-dimensional linear subspaces makes it possible to find such a mapping in randomized polynomial time. By avoiding the moment generating function approach and instead working directly with the distributions of random distance, Authors in were able to increase the lower bound for k. Due to the fact that the conclusion for the lower bound for JL Lemma using L2—L1 norm in (Improving Johnson- Lindenstrauss Lemma) We only consider the scenario when L2—L1 norm is employed, which only applies for random matrices with i.i.d. elements selected from the Guassian distribution and one of the Achlioptas distributions (q = 1,2,3).

Experiment and Result Discussion

Various dimensionality reduction methods, including Multistage Principal Component Analysis, Discrete Anamorphic Stretch Transform, and PCA based on the Johnson-Lindenstrauss Lemma algorithm, have been proposed for use with medical images.

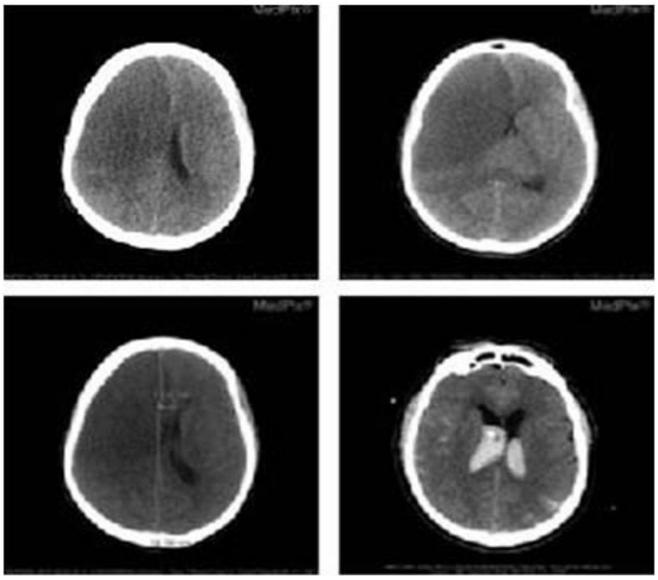

Figure 1: Dimensionality Reduction Techniques for Compressing and Decompressing CT Brain Scans

The proposed method is applied to test pictures in MATLAB and their performance is measured using different parameters. That can also be analyzed through cloud using IoT framework.

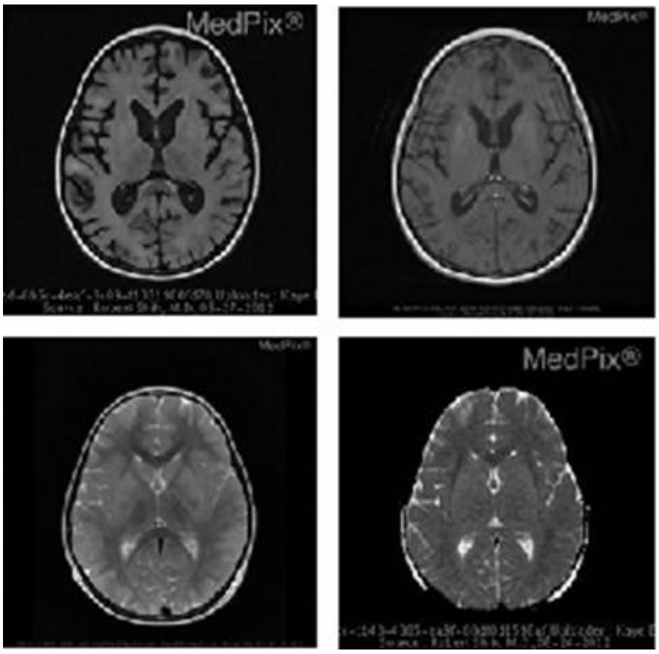

Figure 2: Dimensionality Reduction of (MRI) Brain Scans for Compression and Decompression

Image Database	Evaluation Metrics	Encoding Techniques			
		DCT	Fractal	LZW	Shannon–Fano
CT	PSNR (dB)	24.36	25.87	25.1	26.3
	MSE	522.6	469.15	23.34	257.88
	MAE	9.85	7.5	4.9	5.95
	CR (%)	33.98	33.69	66.59	66.35
MRI	PSNR (dB)	23.88	25.59	25.57	26.46
	MSE	475.3	337.25	247.9	230.88
	MAE	7.98	6.63	5.19	6.75
	CR (%)	33.88	33.8	66.97	66.55

Table 1: Analysis of Principal Components Conducted in Multiple Steps

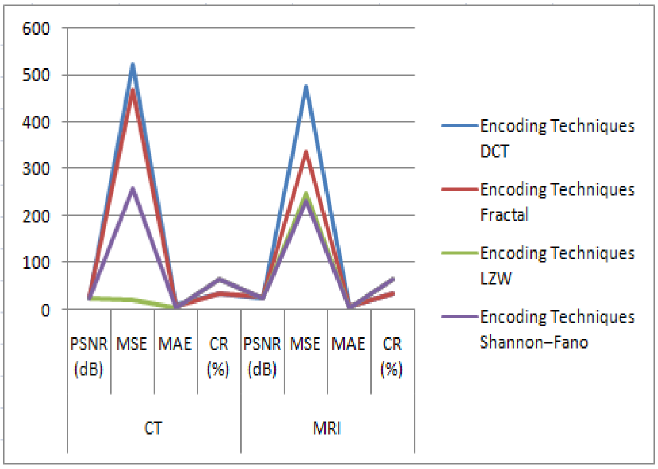

Figure 3: Graphical Presentation of Principal Components Conducted in Multiple Steps

Image Database	Evaluation Metrics	Encoding Techniques			
		DCT	**Fractal**	**LZW**	**Shannon–Fano**
CT	PSNR (dB)	25.12	23.79	24.15	26.99
	MSE	513.3	337.22	298.5	259.88
	MAE	8.86	6.65	5.16	6.95
	CR (%)	33.96	33.65	66.98	66.22
MRI	PSNR (dB)	25.04	24.75	26.32	27.03
	MSE	523.1	210.5	163.5	152.48
	MAE	8.39	5.48	3.9	5.46
	CR (%)	33.98	33.45	66.88	66.18

Table 2: DAST-Obtained Outcomes

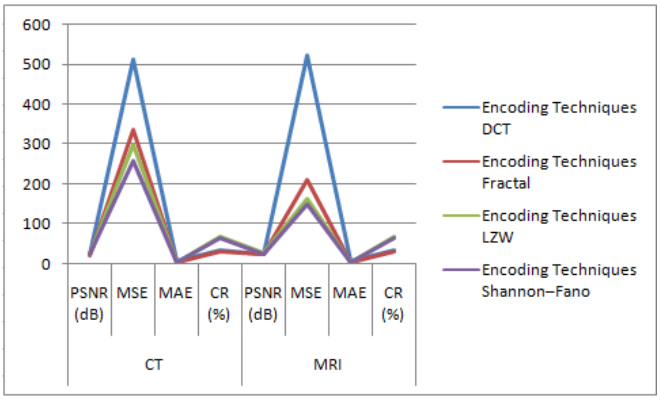

Figure 4: Graphical Reprerësentation of DAST-Obtained Outcomes

Image Database	Evaluation Metrics	Encoding Techniques			
		DCT	**Fractal**	**LZW**	**Shannon–Fano**
CT	PSNR (dB)	25.04	27.35	27.45	28.03
	MSE	316.2	235.79	152.3	114.85
	MAE	6.98	5,69	5.36	4.55
	CR (%)	34.9	34.62	67.86	66.98
MRI	PSNR (dB)	25.35	27.9	28.05	28.85
	MSE	266.8	246.75	158.5	128.47
	MAE	5.99	5.55	5.65	5.15
	CR (%)	34.95	34.76	67.98	67.03

Table 3: Johnson-Lindenstrauss PCA Obtained Outcomes

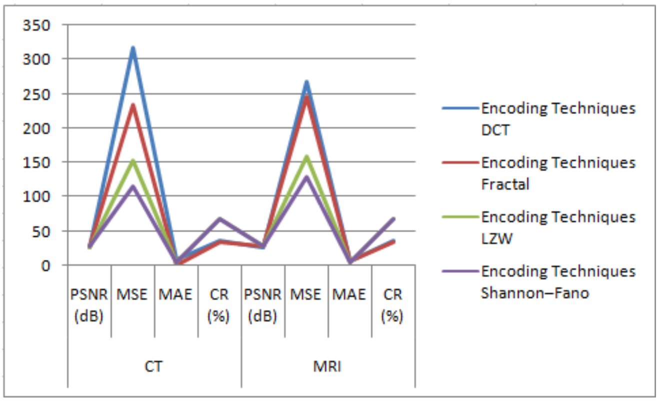

Figure 5: Graphical Representation of Johnson-Lindenstrauss PCA Obtained Outcomes

Figures 1 and 2 display the decompressed picture obtained by dimensionality reduction methods. Tables 1, 2 and 4, as well as figures 3, 4 and 5 show the PSNR, MSE, MAE and CR variations for the various dimensionality reduction methods. The CT images has a PSNR of 28.03 db, whereas the MRI image has a PSNR of 28.85 db. CT images have an MSE of 114.85, whereas MRI images have an MSE of 128.47. CT images have a MAE of 4.55, whereas MRI images have a value of 5.15. Both the CT and MRI images had a compression ratio of 66.98%. When compared to the other article, Johnson-Lindenstrauss PCA Lemma with Shannon-Fano coding yields effective compression.

Conclusion

In this paper, we offer a number of different methods for reducing the number of dimensions in a data set. These methods include Multistage Principal Component Analysis, Discrete Anamorphic Stretch Transform, and PCA using the Johnson-Lindenstrauss Lemma algorithm. The compression of medical images necessitates the use of IOT and machine learning technology. According to the results of the study, compression may be effectively achieved by combining PCA based on the Johnson-Lindenstrauss lemma with Shannon-Fano coding.

In addition, the integration of knowledge transfer from a pretrained model that is not specific to the medical domain has resulted in enhancements to the proposed uagGAN model, leading to increased performance in image translation tasks. The experimental findings demonstrate that the model exhibits efficient performance in translating magnetic resonance (MR) images to computed tomography (CT) images. However, further image augmentation may be necessary when translating from CT to MR.

Future research will focus on the analysis and manipulation of three-dimensional integrated volumes. Our intention is to extend the applicability of the model to include additional forms of MR contrast pictures, including T1 and particle density. At now, the suggested model is undergoing evaluation for the purpose of automating the segmentation of tumors from images obtained by bidirectional MR-CT scans.

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