Storage space reduction in Picture Archiving and Communication System using Generative Adversarial Network

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Research Article

Keywords: Image Compression, Picture Archiving and Communication System, Generative Adversarial Network, Fractal Compression

Posted Date: March 30th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1493530/v1

Abstract

This paper presents a new architecture of Picture Archiving and Communication System based on Conditional Generative Adversarial Network and Fractal Image compression. The Conditional Generative Adversarial Network architecture is based on the Convolutional Neural Network which enables the system to capture the similarity measures without using any handcrafted functions. Performance of the proposed design is evaluated by comparing it with the commonly used compression techniques in Picture Archiving and Communication System such as JPEG, PNG and TIFF. The efficiency of the proposed architecture is tested by using a custom client program that sends the modality images to the Picture Archiving and Communication System server. The simulation runs on computers in multiple networks to gather the data similar to real time healthcare institutions. The results show that the storage space consumption of the proposed design is only 30% in comparison with Picture Archiving and Communication System, which uses the latest Machine learning and conventional non fractal compression methods. It is also observed that the Generative Adversarial Network based Fractal Image compression can drastically reduce the compression time compared to the conventional fractal and non-fractal compression methods. The empirical analysis shows that the proposed Generative Adversarial Network architecture can be a promising method to reduce the space complexity of the system such as Picture Archiving and Communication System.

1 Introduction

Digitalization of radiological images poses a set of challenges that led to the development of a common platform named Picture Archiving and Communi- cation System (PACS) Liu et al. (2003); Dreyer et al. (2006). PACS imple- mentation is targeted to integrate wide varieties of image acquiring devices, storage & display devices and networks. System is designed to cope with large amounts of storage, indexing and data presentation.

Implementation of PACS system in typical health-care institutions de- creases the operational costs, and also facilitate remote and collaborative work among practitioners. Due to the rising demand of PACS, researchers are ex- ploring the possibilities of more flexible and efficient design of the system, such as cloud based storage, automated interpretations and better compres- sion techniques.

Radiology image compression is intended to reduce the data volume from different radiology image modalities. This leads to an improvement on storage space management and transmission bandwidth requirements without any recognizable reduction in the image quality. The advancements in the various high volume imaging modalities cause the PACS to outstrip the use of lossless compression schemes. Hence, the need of an efficient lossy compression scheme is getting increased day by day. The existing implementation of PACS uses compression techniques such as JPEG Marcellin et al. (2000), PNG Roelofs (1999) and TIFF Parsons and Rafferty (2002). These methods are able to achieve a good compression ratio as they all are highly lossy schemes. But in the case of radiology images, the fine structural change in the images may cause the healthcare professional to interpret the image differently and cause an incorrect diagnosis. So the above mentioned methods are used in the PACS system with minimal loss of data, causes more consumption of storage space. Fractal based image compression (FIC), which is a lossy compression scheme proves its efficiency for images which exhibits self-similarity Fisher (1994).

Fractal Image Compression is a lossy compression scheme promoted by Barnsley and was automated by Jacquin Jacquin (1992). The underlying concept is that every image exhibits a certain level of self-similarity or affine redundancy. The basic idea is to represent an image by using a contractive transform and make its fixed point is too close to the original image Fisher et al. (1992). The segmented small size block, called Range block is approximated to the large block, called Domain block to get the fractal transformations Fisher (1995). This leads to an increase in the computational complexity and hence the encoding time. But the compression ratio, rate distortion factor and the decoding complexity which FIC exhibits significantly better than other non- fractal conventional algorithms like JPEG, TIFF and PNG. Hence, majority of the research works in this domain focus mainly on reducing the matching complexities involved in finding the precise affine transformations.

A wide variety of partitions like fixed size square blocks, quad tree, HV partitioning, irregular regions, polygonal blocks and overlapped blocks has been introduced to speed up the encoding process Wohlberg and Jager (1999). The performance analysis of these algorithms show that the quad tree partitioning offers better rate distortion values than others. HV partitioning performs better than quad tree and irregular regions works well than fixed size square blocks Wohlberg (1996). Another critical metric in influencing the speed of the Domain-Range matching is the type of transform, as it determines the convergence factor while decoding the compressed image. The possible types are block transforms and those transforms apply over pixel values. The algorithms introduced to reduce the time complexity of the encoding process are categorized into classification based, feature vector based and machine learning based approaches Roy et al. (2018).

Medical images exhibit a better similarity pattern than other large sized images like satellite images. Hence, the FIC can be a better method to save storage space and transmission bandwidth in a PACS based system. Even if the fractal based compression provides a better compression ratio, the time complexity of the encoding algorithm is NP Hard Liu et al. (2019). With the use of classical approaches of FIC in PACS, compression of the modality images consumes more time and computational resources.

To analyze the performance of the proposed system against the machine learning base compression algorithms, we have chosen and implemented three prime learning methods. Zhengxue Cheng and et.al Cheng et al. (2020) use Gaussian mixture models (GMM) to represent the codes in the compres- sion.This attempt led to an accurate and flexible entropy model.The experi- ment shows that it performs better in Kodak and high resolution data sets.The iWave ++, an algorithm developed by Haichuan Ma and et.al is trained to use wavelet-like transform to convert images into coefficients without any loss of information Ma et al. (2019). Empirical analysis shows that on Kodak data set, iWave++ is able to save 17.34% bits over Better Portable Graphics (BPG) compression. A novel Non-Local Attention optimization and

Improved Con- text modeling-based image compression (NLAIC) algorithm is proposed by Tong Chen and et.al Chen et al. (2021), that uses a deep neural network based on variational autoencoder to encode the image. This method outper- formed the conventional compression schemes such as BPG, JPEG2000 and JPEG. Vijayshri Chaurasia presents a novel method to speed up the fractal compression Chaurasia and Chaurasia (2016). It uses feature extraction as the primary method to avoid the exhaustive search.

The contributions of this work are summarized as follows:

1. A Conditional GAN (CGAN) Yi et al. (2019); Durall et al. (2020); Ag- garwal et al. (2021); Mirza and Osindero (2014) based compression algorithm is proposed. The CGAN predicts the affine transformations require for the fractal compression, after the completion of the learning phase.
2. A flexible design of the PACS that incorporates multiple storage mechanisms is also proposed. The new design allows the user to plug-in any new storage technique, which enables a researcher to test its efficiency.

Followed by this introduction, the rest of the paper is structured as follows. Section 2 presents the details of the proposed system including the design of new PACS and CGAN. Section 3 discusses the experimental setup, metrics used to evaluate the system and its results. Section 4 concludes the paper.

2 Proposed System

Radiology department of the hospital generates thousands of images in a day that are captured through different modalities such as Magnetic reso- nance imaging(MRI) Mcrobbie et al. (2017), Computed Tomography (CT) scan Hsieh (2003), Ultrasonography (USG) Chan and Perlas (2011) etc. In a typical installation, the storage requirements of PACS is very high compared to the other software such as the Hospital Information system (HIS) Lepanto et al. (2006) Bakker et al. (1991). Images generated from the radiology depart- ment contribute the largest segment of the patient data Liu et al. (2003) Arm- brust (2009); Nagy and Farmer (2004). Hence, the backup and retrieval of the historic modality images also poses a challenging problem. A typical PACS installation uses compression techniques such as JPEG, PNG or TIFF. But these methods do not consider the main property of medical images such as structural similarity of the modality, while compressing the image. Hence, the recommended method for saving the storage space in PACS is a compression technique that utilizes the structural similarity of the images without losing the fine information.

Fractal compression methods are widely known for its property of utilizing the structural similarity of the image with the highest compression ratio. But the classical method of fractal compression suffers from the time complexity of the compression process. In this paper, a method is proposed which utilizes GAN in adjacent with the IFS to achieve lesser time complexity and better compression ratio without losing any information from the modality images. The proposed system uses a modified version of an open source PACS implemented by Costa et.al Costa et al. (2011).

[Fig. 1 about here.]

Figure 1 shows the functional overview of the proposed system. The system mainly comprises an end point for receiving modality data based on Digital Imaging and Communications in Medicine (DICOM) Pianykh (2012); Benson and Grieve (2016), storage mechanism and a retrieval mechanism. All the image acquisition systems in a hospital require storage and support of DICOM for sending data to the receiving end over a TCP/IP network. The received data is sent to the PACS framework using the HTTP REST Mumbaikar and Padiya (2013) Application Program Interface (API). The frame-work selects the suitable compression mechanism from the storage plug-in system.

Radiology information system (RIS) and HIS provide the relevant metadata about the patient details, and stored in a separate Relational Database Management System (RDBMS) to provide an easy search index Sumathi and Esakkirajan (2007); Giuse and Kuhn (2001). The following sections describe the details about the DICOM, compression techniques and retrieval mechanism in the proposed PACS architecture.

2.1 Digital Imaging and Communications Medicine

DICOM is considered as the golden standard of communication in the Radi- ology department network Mildenberger et al. (2002). Majority of the device vendors provide an end point for their devices that support DICOM over TCP/IP network. DICOM specifies a data format that includes the patient information such as hospital ID and a set of services to store and retrieve the modality images. All services define a set of protocol words to establish, send and receive the data. PACS framework hosts a central service that defines the DICOM standard and all other capturing devices communicate with PACS through the service interface.

2.2 Conditional Generative Adversarial Networks (CGAN)

Generative Adversarial Networks are rarely used in the field of image com- pression. It is because of the use of learned compression methods in recent years researchers are exploring the possibility of using GAN to compress the image. GAN can be modified to a conditional model if both generator G and discriminator D are conditioned using some extra information *y*. Conditional input *y* can be any information that is related to the sample image *x*. It may be a different vector space representation of *y* or a class information about *y*. CGAN modifies the GAN by feeding **y** into both generator and discriminator as an additional input layer. In the generator, the latent space vector *z* is combined with *y* joined to form a new input representation.

The generator is receiving the data that is joined to the hidden repre- sentation of the latent space vector and the conditional input y. Then the equation for value function V for the min-max game between Generator and discriminator is given in Equation (1).

$$\min_{G} \max_{D} V(D, tt) = E_{x \sim pdata(x)} [\log D(x|y)] + E_{z \sim pz(z)} [\log(1 - D(tt(z|y)))] \quad (1)$$

2.3 Fractal Compression using CGAN

We propose a CGAN based system for fractal compression. The objective of the system is to enable the FIC to learn the particular type of images such as medical images from a training data set that include the raw image and the corresponding fractal compressed data. Consider a set of pixels x with size n, that is chosen from the input image. The purpose of FIC is to find the pixel sets $X_t$that have a high self-similarity to x. Whereas, t represents the affine transformation sequence that can be applied to the x to obtain a member in X_t. The affine transformations include translation, rotation, shearing and scaling of the input set and M_t,M_r,M_h& $M_s$are the respective affine transformation matrices. For example, a transformed pixel set can be obtained by M_s*(M_t*x), where x is the input pixel set.

A classical fractal compression algorithm tries to find the best suited transformation t, by grouping pixels and measuring the similarity between the groups. Once the comparison returns a better similarity between two groups of pixels, the corresponding transformation matrices and their order of application is used to represent the set of pixels. This exhaustive search for the similar group of pixels after applying every possible combination of affine transformation causes exponential increase in execution time. To reduce the time complexity, we have to introduce any boundary condition to stop the search. But the majority of the recent research in this area proposes a boundary that reduces the search time by restricting the search set or similarity measures. Hence, our objective is to reduce the time complexity by applying a method that doesn't interfere with similarity measures or compression ratio of the fractal compression. To achieve that goal, we select the images in specific domains that keep more similarities across a set of images. In the case of medical images, the modalities generated from the data acquisition system is used for radio diagnosis in health care systems such as MRI and CT. So these images show a very high self similarly and can be captured using machine learning algorithms.

The architecture of CGAN based FIC is inspired by the pix2pix architec- ture developed by Isola, Phillip and et al. Isola (2017). Generator is a modified version of the U-Net architecture Ronneberger et al. (2015) and Discriminator is a convolutional PatchGAN Yang (2017). All these architectures are based on the Deep Convolutional Network. The architecture of both generator and discriminator is shown in Figure 2.

[Fig. 2 about here.]

The generator consists of an encoder and decoder. The encoder down samples the image to a lower size vector and the decoder up samples it to the transformation sequences. The encoder consists of a sequence of convo- lutional and batch normalization layers with leaky ReLU activation. Decoder is a sequence of transposed convolution, batch normalization, dropout and ReLU. The FIC works similar to pix2pix except the nature of the output. The output is the transformation sequence in FIC instead of an image in pix2pix.

2.4 Network Training and Predictions

In GAN, the network loss makes it adapt to the data set. But in CGAN, it learns from the loss, which is the difference between the output of the generator and the true target. The generator loss is sigmoid cross entropy loss between the generated transformations and array of ones. The total loss used to calculate the gradients is given Equation (2), where MSE is the mean squared error and lambda is a constant that bias the learning.

$$Total\ Loss = ttenerator\ loss + Lambda * MSE\ (true\ transformations,\ generated\ transformations) \quad (2)$$

[Fig. 3 about here.]

In the case of discriminator, it calculates the loss from the true transforma- tions and generated transformations. The total loss in discriminator training is given in Equation (3).

Total loss = *sigmoid cross entropy* (*true transformations, array of ones*) +*sigmoid cross entropy* (*generated transformations, array of zeros*) (3)

[Fig. 4 about here.]

Sigmoid is a cross entropy that can be obtained by applying sigmoid function to the signal before the cross entropy. Figure 3 and Figure 4 shows the process of loss calculation in the training of generator and discriminator. To achieve better accuracy on transformation predictions, CGAN has to see a large number of samples in the training process. 5000 samples from the Internet Brain Segmentation Repository (IBSR) are considered for empirical analysis. Each raw image sample X is processed by the classical fractal image compression algorithm to generate the transformations. The transformations T from the classical algorithm and sample X are considered to be the input sample (X, T) for the CGAN training. Once the training process is completed, a set of sample data different from the training samples are used to test the network prediction.

2.5 Process flow

Figure 5 shows the process flow of the proposed system. The system receives the data from a capture device through DICOM and checks for the metadata information. If the details are not available in the DICOM data, it retrieve the details from the HIS. Image data is compressed using the proposed compression technique and store it in the file storage or a cloud base Silva et al. (2012) storage. File information and patient details are stored in a predefined RDBMS Phaneendra and Reddy (2018) .

Figure 6 shows the process flow of retrieval mechanism from the PACS. The user requests an image using a specific query that indicates the patient id and a selected date. The retrieval client posts the request to the queue of PACS. The queue is implemented to handle multiple requests at the same time. The PACS fetches the patient details from the RDMS server and compressed images from the file storage. Transformations fetched from the file storage reproduce the original image by applying the decompression algorithm. Once the decompression is completed, the PACS generates the corresponding DICOM file and reply back to the retrieval client.

[Fig. 5 about here.]

[Fig. 6 about here.]

3 Result And Discussions

In this section, performance analysis of the modifications proposed in the existing PACS system is done by simulating various modality images and its respective hospital metadata. Subsequently, the method is compared with legacy non-fractal methods, feature based fractal compression method and three other novel machine learning based compression methods.

3.1 Experimental Set up

The experimental setup of the proposed system includes an installation of the PACS system with custom storage plugin to support the CGAN based fractal compression technique. The hardware configuration of the system includes Intel Xeon processor, 4TB SSD Hard Disk, 8GB RAM and 1 Gb/s network. A custom client program is developed to generate the DICOM files from an existing set of modality images and send them to the PACS from different computers residing on the PACS network. The program is designed to send multiple images at a time over TCP/IP using an application protocol based on DICOM. A web based User Interface (UI) has been developed to configure and send the user query. The interface is able to display the retrieval time, compressed size and original size of the image modality. Sample screenshot of the interface is shown in Figure 7. GAN is trained using the IBSR data set Frazier et al. (1910).

The image modalities used in the empirical analysis are MRI, CT and USG. The compression time, retrieval time, compression ratio, storage space, PSNR and SSIM of the test images are recorded. The experiment is repeated with image size starting from 1 MB to 30MB. The GAN network is also trained using different epochs starting from 100 to 1000 with batch size of 1000.

[Fig. 7 about here.]

3.2 Performance metrics

The indices used to evaluate the performance of the proposed method are described as follows.

1. Storage space over time: It indicates the amount of space required to store the compressed data in the PACS Server over a long time period. Depending upon the server configuration, the storage may present in remote locations such as a cloud service.
2. Execution time: It indicates the time required to complete the compres- sion process excluding the storage read and write operation time.
3. Epochs: This metric is used to indicate the number of times the training algorithm has seen the data set.

4. Accuracy: It measures the correctness of prediction of transformations by GAN in a subset of the data set.
5. Peak Signal to Noise Ratio (PSNR): It indicates the quality of the reconstruction of the modality image. It is expressed in terms of Mean squared error.
6. Space Saving (SS): Space saving shows the amount of space that can be saved while using the compression technique. It can be derived from the equation, *ss* = 1 (*Compressed Image size/Uncompressed Image size*)
7. Structural Similarity Index Measure (SSIM): SSIM refers to the simi-larity in structures between the two images. In the case of image compression, SSIM works as a metric that indicates the change in structure of the com- pressed image.
8. Retrieval time: It is the time taken to retrieve an image from the PACS server and display it into the client machine.

3.3 Discussions

Following sections discuss the different experiments conducted to evaluate the proposed system.

3.3.1 Evaluation of the GAN Training process

CGAN is trained using openFMRI 138 (2013) MRI data set, TCIA Clark et al. (2013) computed tomography data set and Open CAS Wunderling et al. (2017) Ultrasonography data set. Training process involves feeding the network with uncompressed images and fractal compressed images in batches. The prediction for a test set is evaluated in terms of PSNR and SSIM in an interval of 1000 images. Figure 8 shows the results from evaluation of the prediction process. It is observed that the SSIM and PSNR of the predicted images increase correspondingly to the training data set size.

A cross evaluation of the same network is performed using a different test set from ImageNet Deng et al. (2009), that consists of natural images. Figure 9 shows the results obtained from the cross evaluation process. It has been observed that PSNR and SSIM of the predicted image is significantly low in comparison with the test set of MRI images. The evaluation process has clearly indicates that, we cannot use a network trained for a specific category of image for any other categories.

3.3.2 Evaluation of the Compression process

The compression process is evaluated by both qualitative metrics such as SSIM and PSNR, and the quantitative metrics such as execution time and space- saving. Qualitative metrics indicate the quality of the images after decoding a compressed image and shows how visually impressive the image is to the human visual system.

Quantitative metrics show how much the method can save storage space and execution time while compressing a raw image. These metrics have a direct impact on the investment cost of resources such as storage solutions and computing infrastructure.

Comparison between proposed method and non-fractal methods in terms of PSNR, SSIM and Space saving is shown in Figure 10 (a-c). It is observed that the PSNR and SSIM of the proposed method is higher than the popular non fractal generic compression algorithms like JPEG, PNG and TIFF. Figure 10 (d-f) shows the changes in PSNR, SSIM and Space savings in comparison with all the aforesaid machine learning based compression methods. For a 15 Mb file size, the performance of the proposed system in terms of PSNR is at par with competing machine learning based compression techniques. In the case of SSIM, it performs better than the machine learning based techniques. It is also observed that the space-saving offered by the proposed system is 40% to 75% less than the machine learning based compression methods

[Table 1 about here.]

[Fig. 8 about here.]

[Fig. 9 about here.]

[Fig. 10 about here.]

[Fig. 11 about here.]

[Fig. 12 about here.]

[Fig. 13 about here.]

[Fig. 14 about here.]

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Storage space : Figure 11 shows the usage of the storage space required for the PACS server after compressing the modality images. Same input raw image is compressed using JPEG, PNG, TIFF and the proposed method Parsons and Rafferty (2002). The raw image size is varied from 1Mb to 30Mb. It is noted from the graph that the proposed method takes less space, compared to the competing methods. To observe the growth of the data size

in real time scenarios, 300 images are sent to the PACS in every minute. In a small scale hospital, our considerations are 300 modality images are generated in a day, the network supports 1G/s speed and no storage restrictions. In the simulation process, 1 minute is treated as equivalent to a day. The total storage consumed in PACS is noted for every 3 months. Figure 12 shows the consumption of storage up to 1 year for different compression methods. It is observed that the storage space requirements of the proposed algorithm over a year is only one third of the conventional compression algorithms like JPEG, PNG and TIFF.

Accuracy: Accuracy of the prediction of transformation is measured against the number of epochs, a system encounters during the training phase. Figure 13 shows the corresponding improvement in the accuracy with respect to the number of epochs. It has been noted that the prediction accuracy of the system improves as the increase with an epoch during the learning phase. But the accuracy becomes stagnant after 900 epochs.

shows the comparison of execution time of the feature based fractal compression and proposed method. Proposed method shows a significant reduction in execution time compared to the competing method. It is also observed that time complexity of the proposed algorithm is proportional to the size of the image.

4 Conclusion

Computational time complexity of fractal compression algorithms is one of the major setback that blocks the adoption of FIC from all major data storage techniques. But the use of fractal compression techniques as the primary image storage format can have a significant impact on the reduction of storage space and cost in an exponentially growing system like PACS.

In this work, a novel image compression algorithm based on fractal trans- formations has been proposed to replace the use of traditional algorithms in PACS server. The proposed method uses GAN based fractal compression algo- rithm to reduce the storage space in the PACS server. The reduction in size of the images without losing its quality, contributes to the improvement in PACS network traffic, reduce network bandwidth requirements and less blacked stor- age space. The exhaustive testing of the proposed algorithm shows that the storage space requirement is 70% less than JPEG, over a year. This reduction in space impacts the backup and remote storage requirements of PACS, which is considered to be very crucial in storing the required data of patients for long duration.

The proposed system can be expanded further to the domain of video compression. Major considerations on the portability of the proposed system for video compression methods which include time as a new dimension, which provides abundant options for learning scenarios. The existing video compression standards such as H.265 has already included a similar analysis to provide compression but not with a fractal similarity method. The proposed system can also be utilized to compress the audio files, if we treated it as a frame based on time. The audio files show the fundamental property of the iterated function system, because of the repetitions in the sound. So the proposed method can be a promising method for audio compression.

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Tables

Table 1 Performance comparison of proposed method and traditional algorithms used in PACS.

Raw image size (Mb)	Compression Method	Compression time(ms)	Compressed Size(Mb)	PSNR	PACS Retrieval time(ms)
	Proposed method	10	0.4	40	101
	Feature based	122	0.6	40	121
1	JPEG	20	0.5	32	133
	PNG	21	0.6	33	183
	TIFF	21	0.8	33	178
	Proposed method	200	5	41	250
	Feature based	700	5.6	42	271
10	JPEG	260	7	59	339
	PNG	310	7.3	62	410
	TIFF	244	8	83	443
	Proposed method	400	11	39	605
	Feature based	1600	11.2	39	611
20	JPEG	560	14	28	902
	PNG	800	14	26	1251
	TIFF	640	16	26	1406
	Proposed method	550	19	42	1005
	Feature based	2400	20	41	1108
30	JPEG	800	28	31	2019
	PNG	880	27	28	2311
	TIFF	950	26	33	2862

Figures

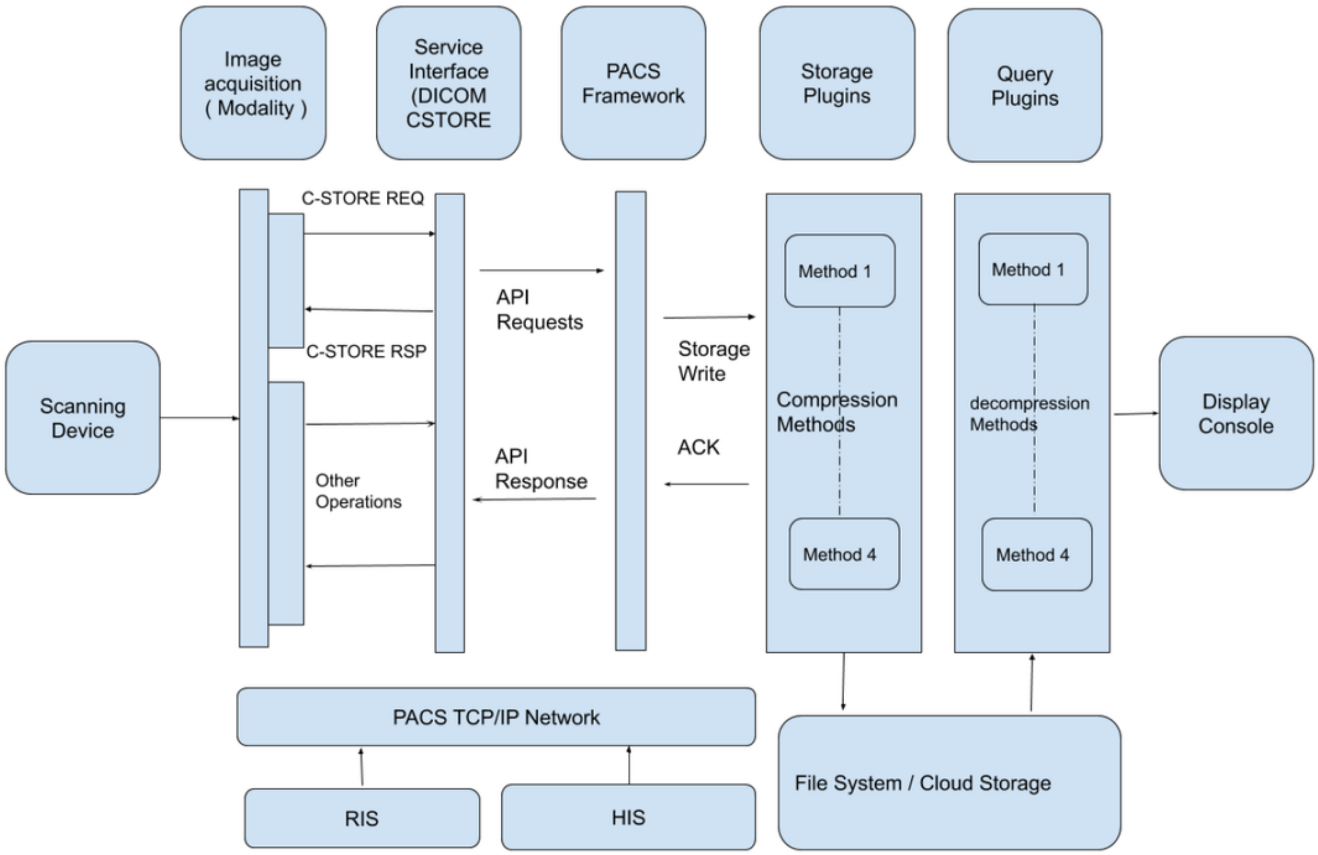

Figure 1

Architecture of the proposed PACS

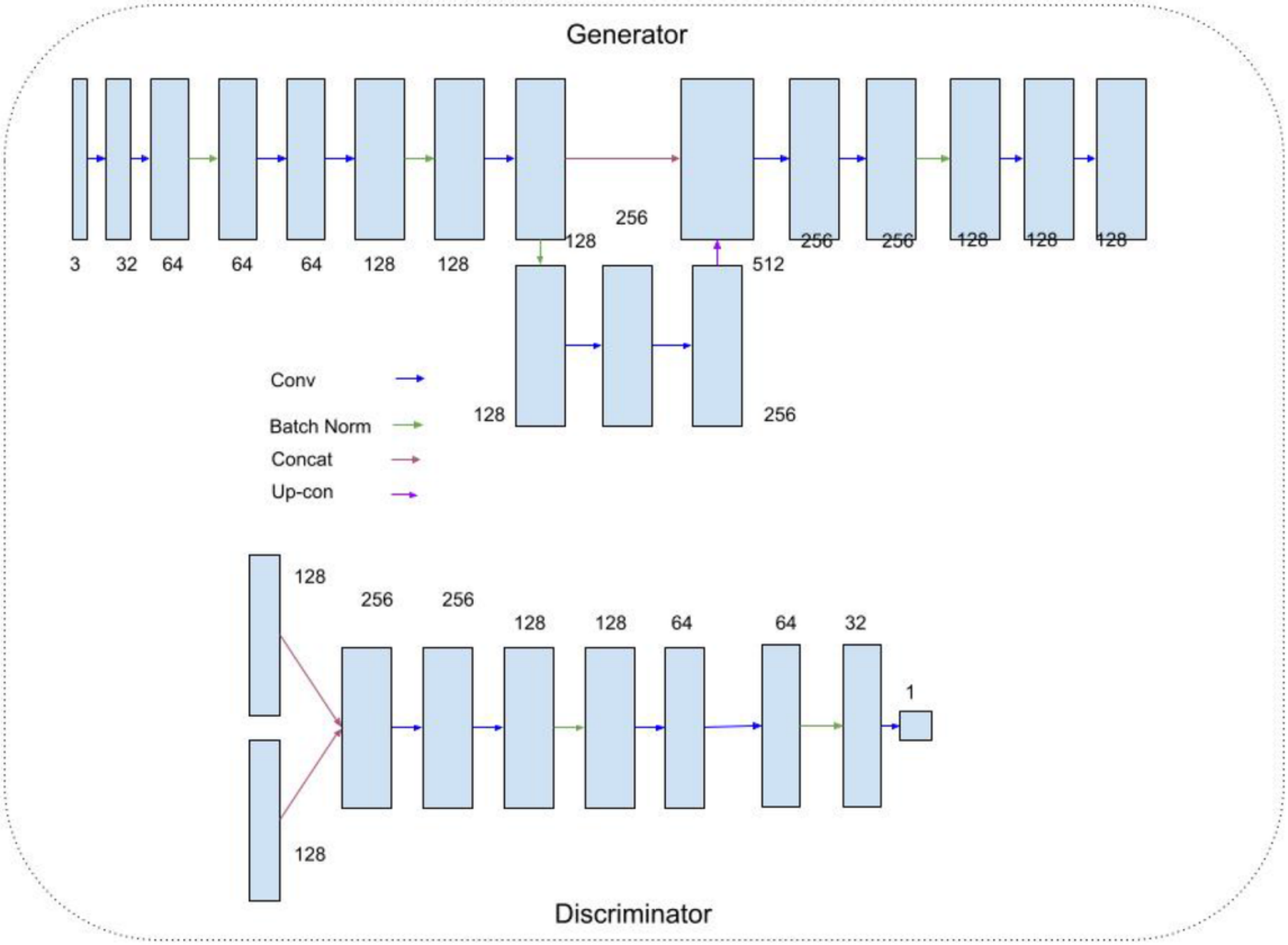

Figure 2

Layered architecture of the CGAN used for Fractal compression

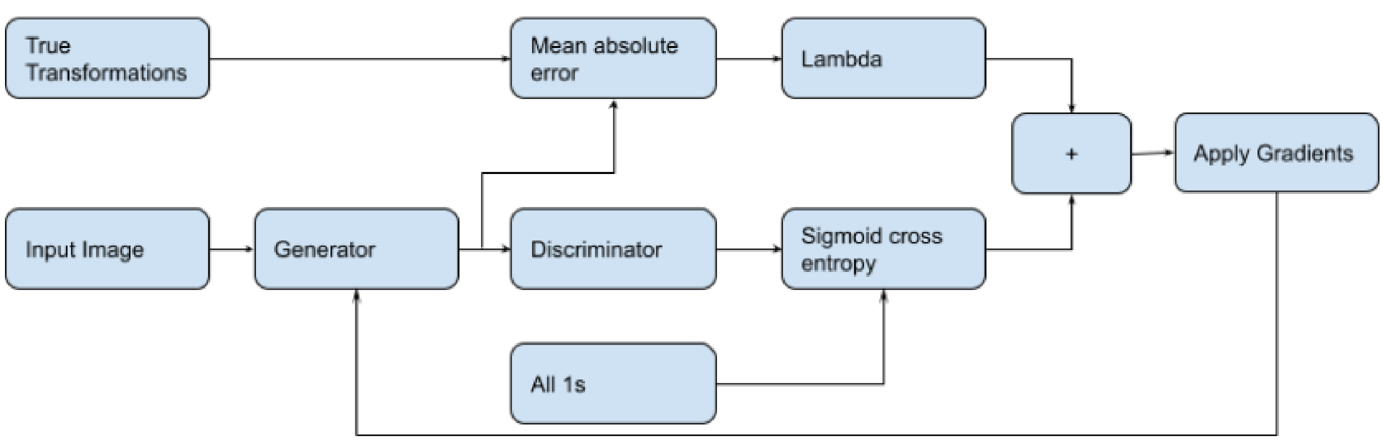

Figure 3

Calculation of the Generator loss.

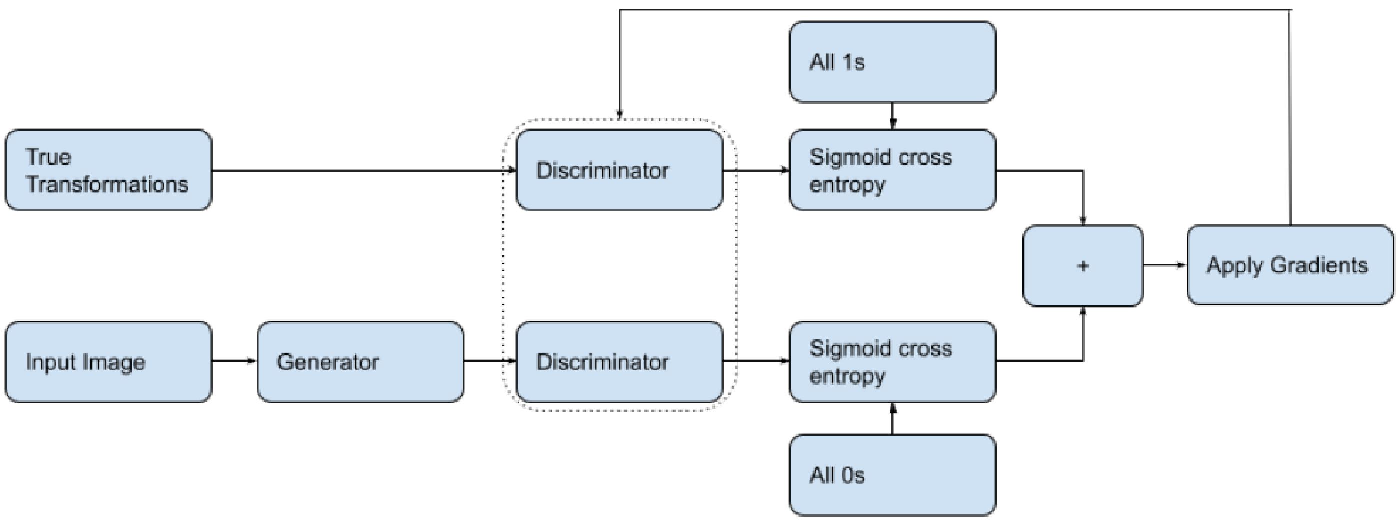

Figure 4

Calculation of the Discriminator loss.

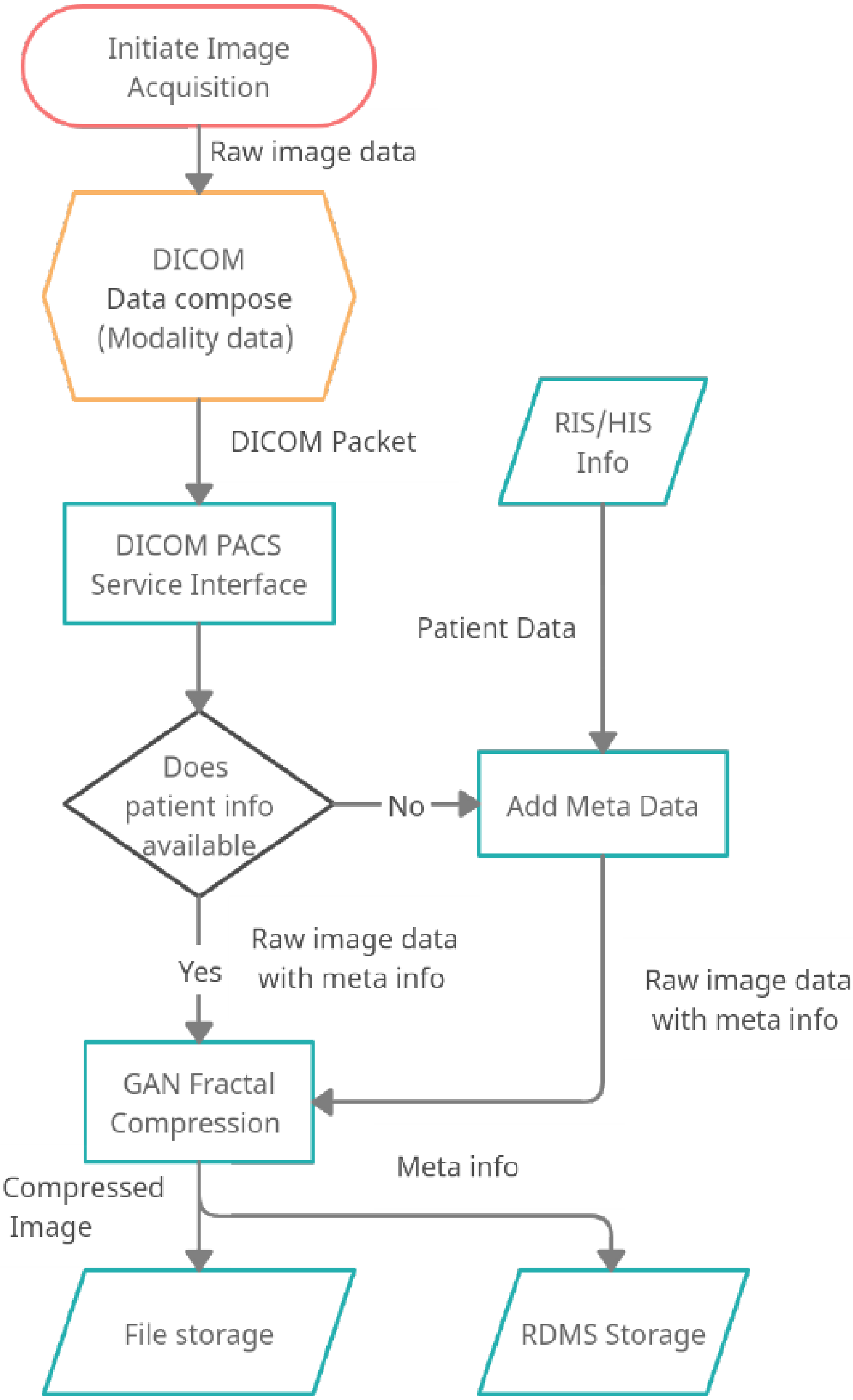

Figure 5

Process flow from modality acquisition to PACS storage

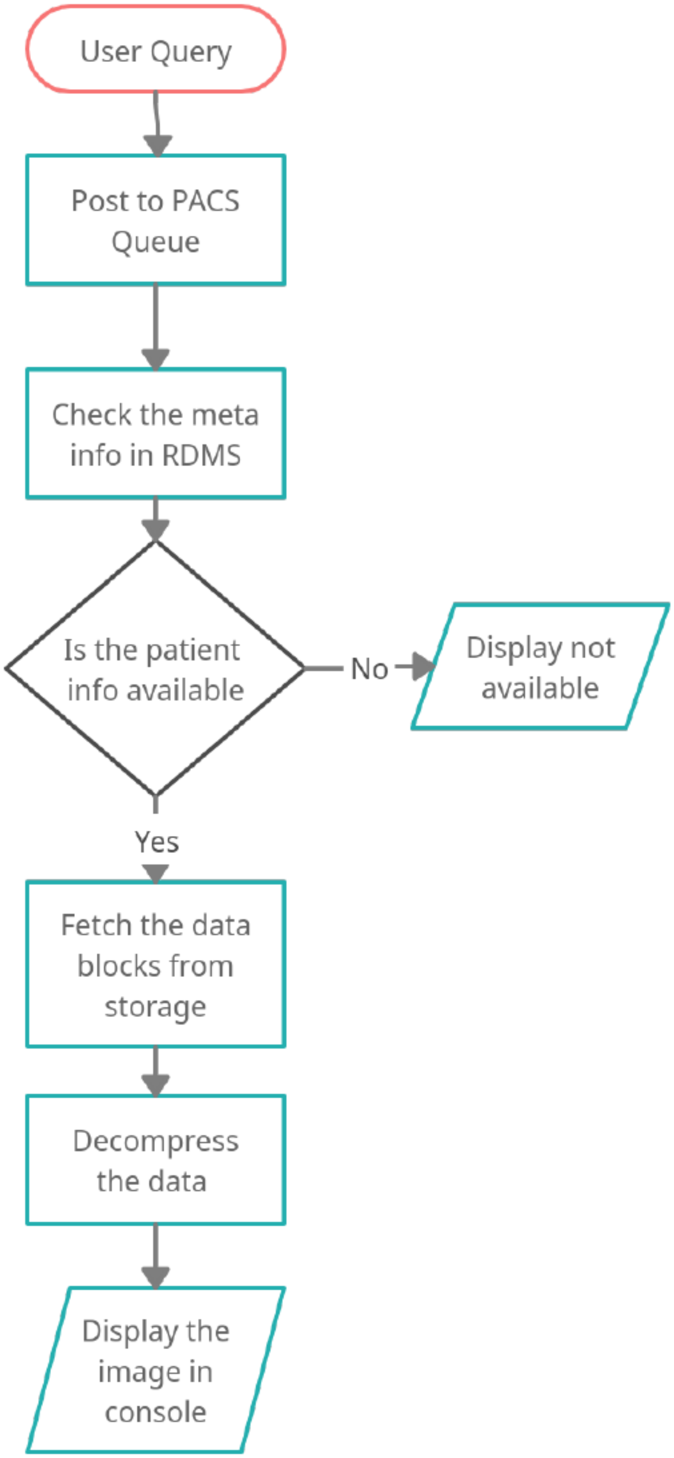

Figure 6

Process flow to retrieve an image from PACS

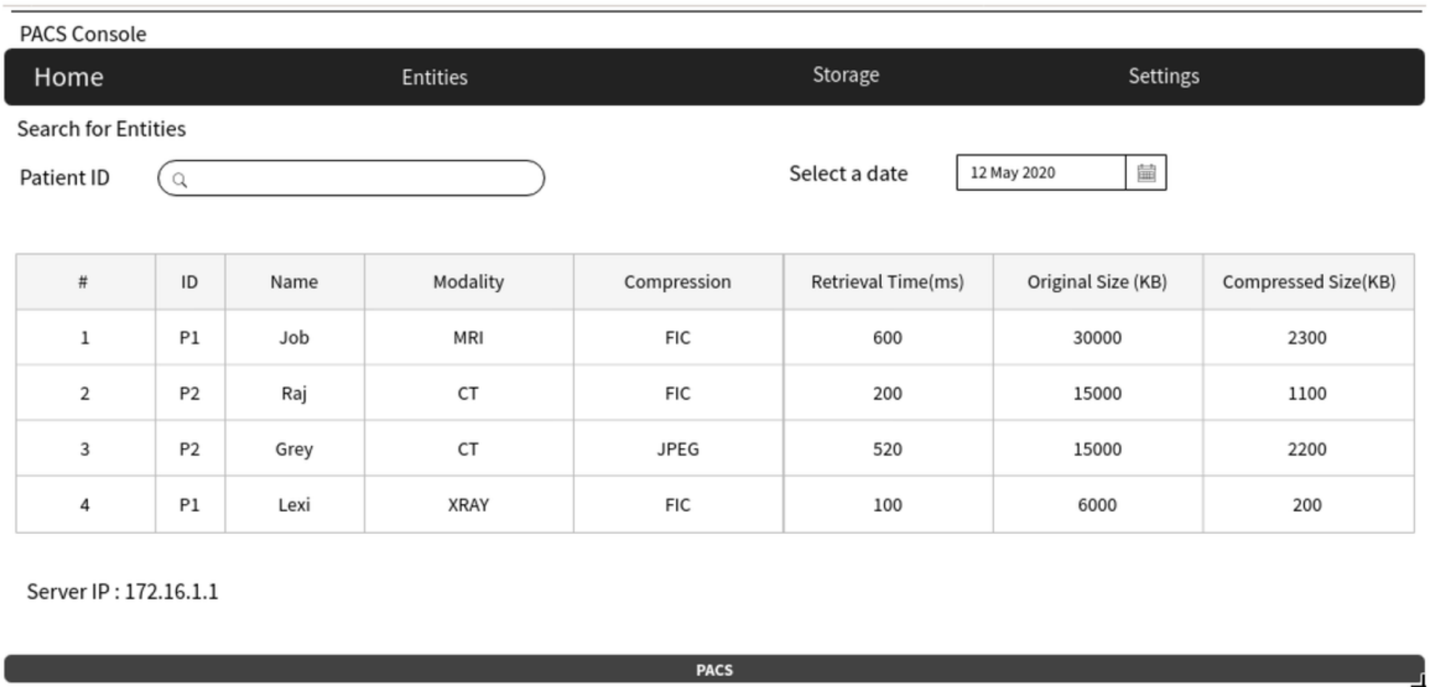

Figure 7

User interface (UI) of the proposed PACS

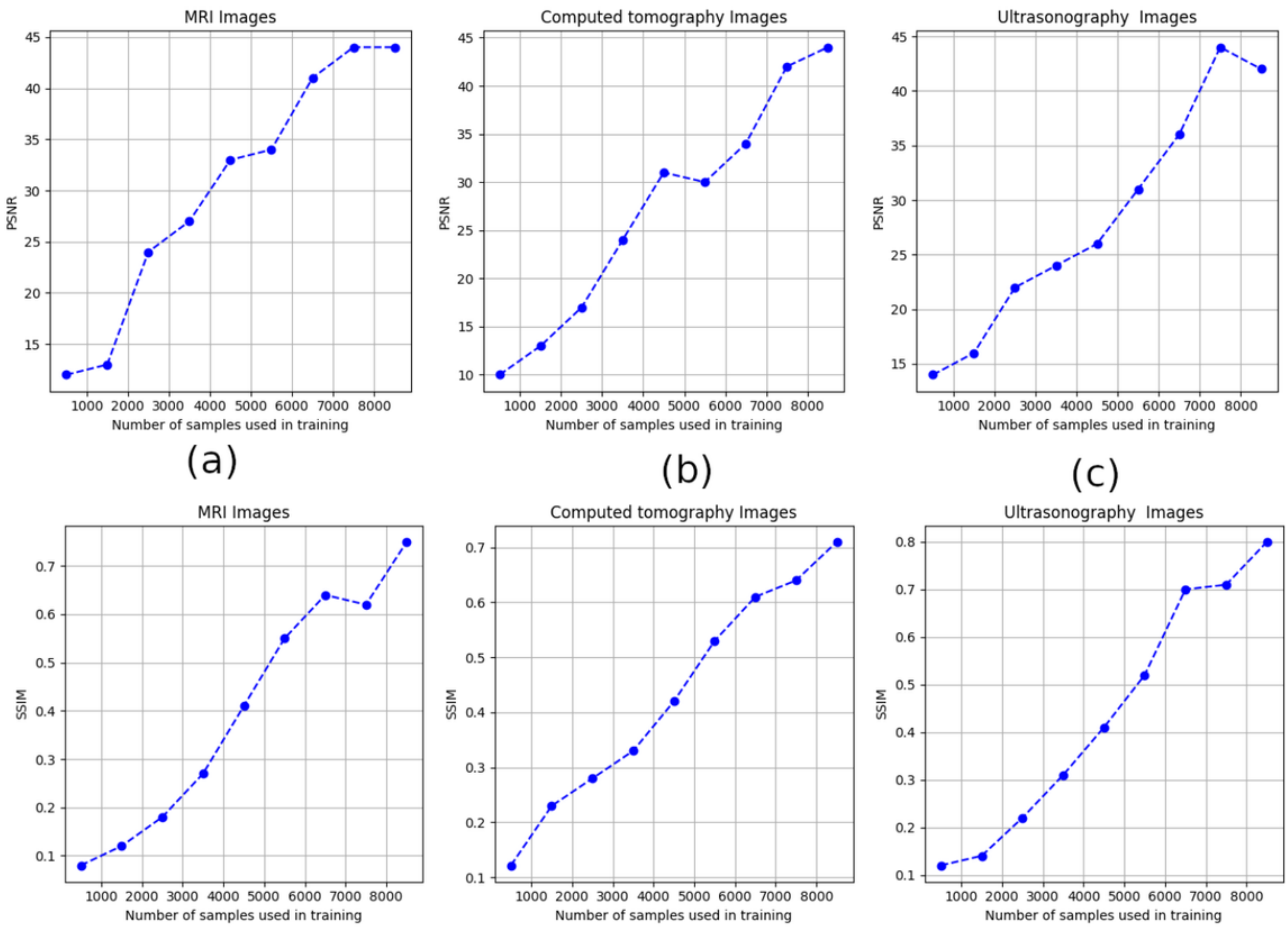

Figure 8

Variation in PSNR and SSIM of predicted MRI, CT and USG images with respect to the number of training samples.

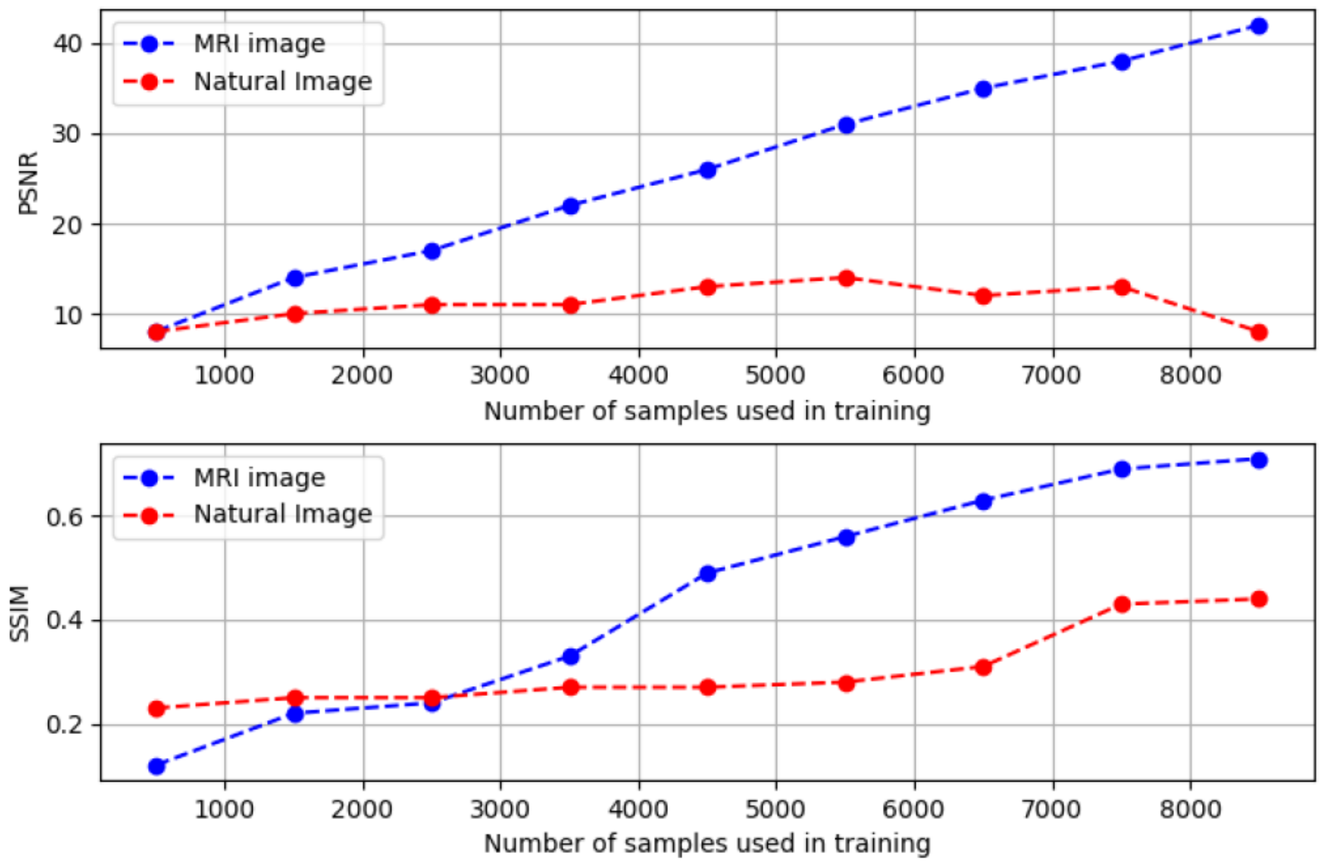

Figure 9

Cross evaluation of the proposed system using natural images from ImageNet.

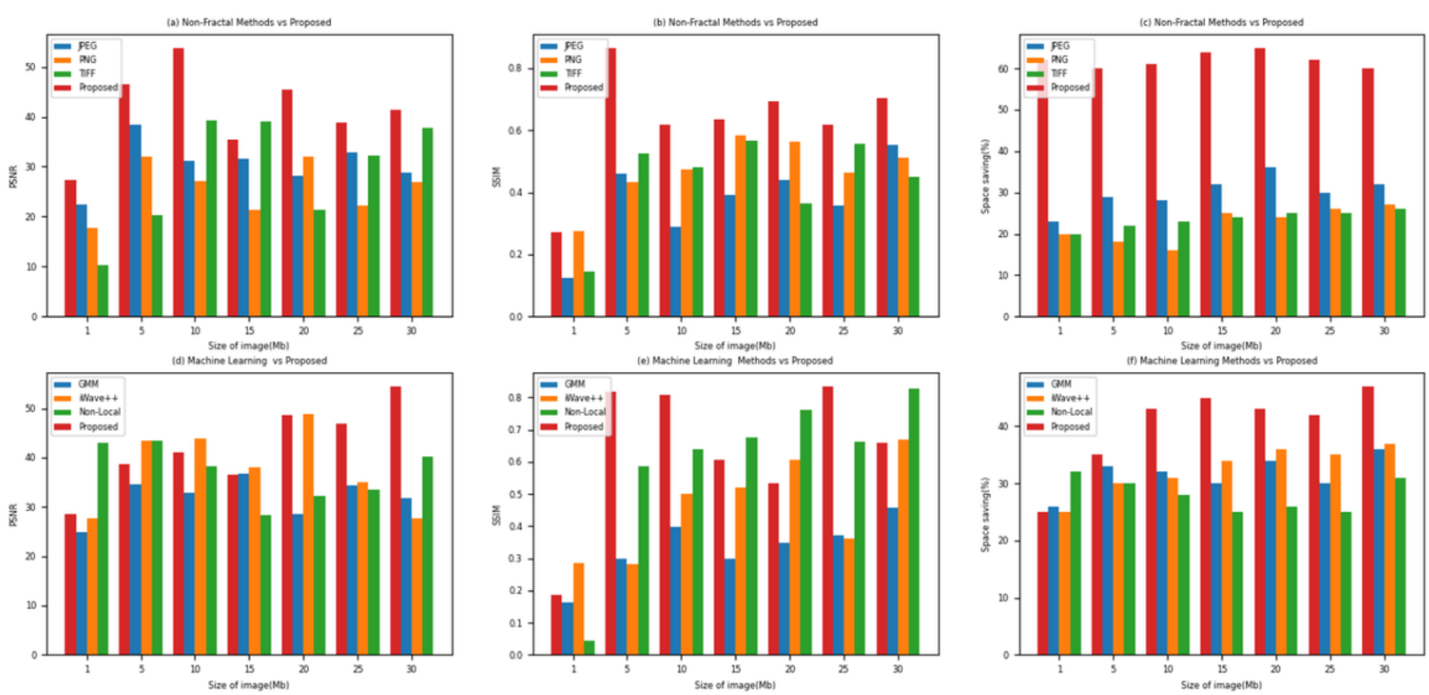

Figure 10

(a-c) Comparison between proposed method and non-fractal methods in terms of PSNR, SSIM and Space saving. (d-f) Comparison between proposed method and machine learning methods in terms of PSNR, SSIM and Space saving.

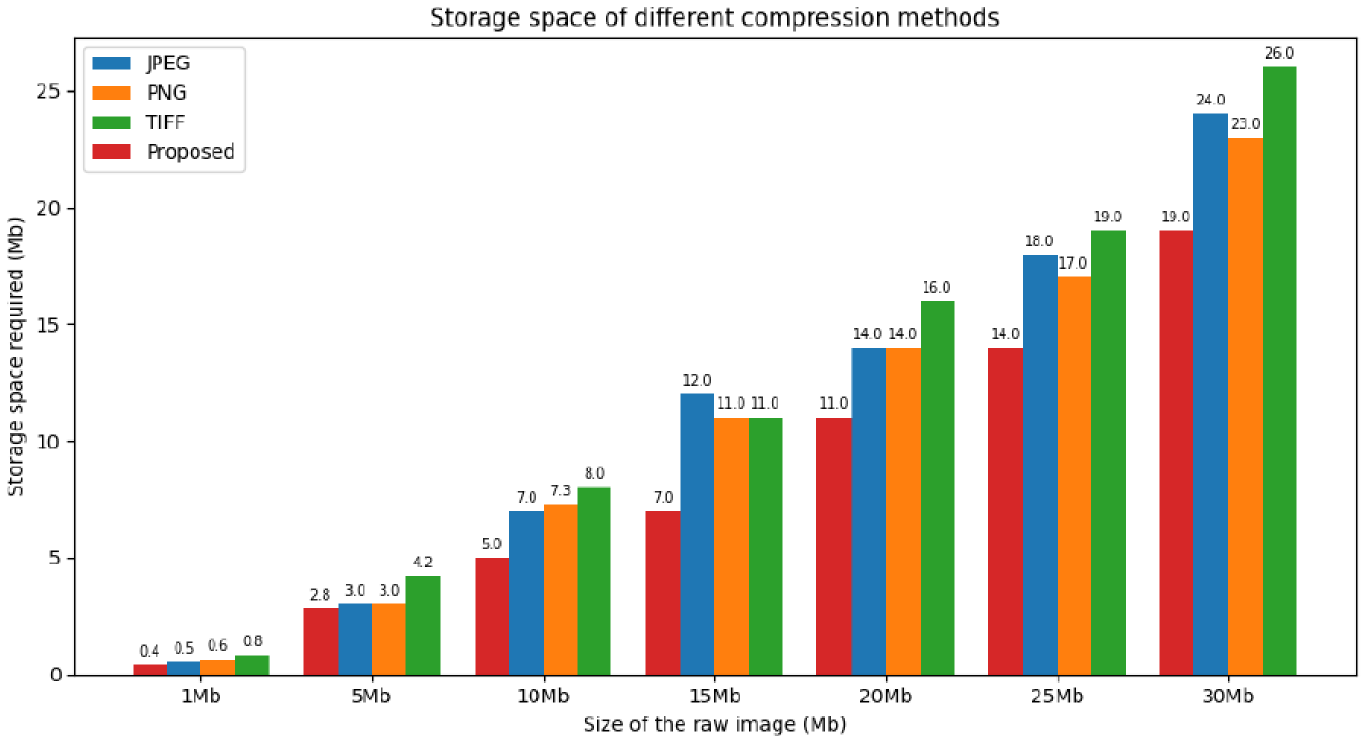

Figure 11

Storage space requirements of different algorithms for various image sizes

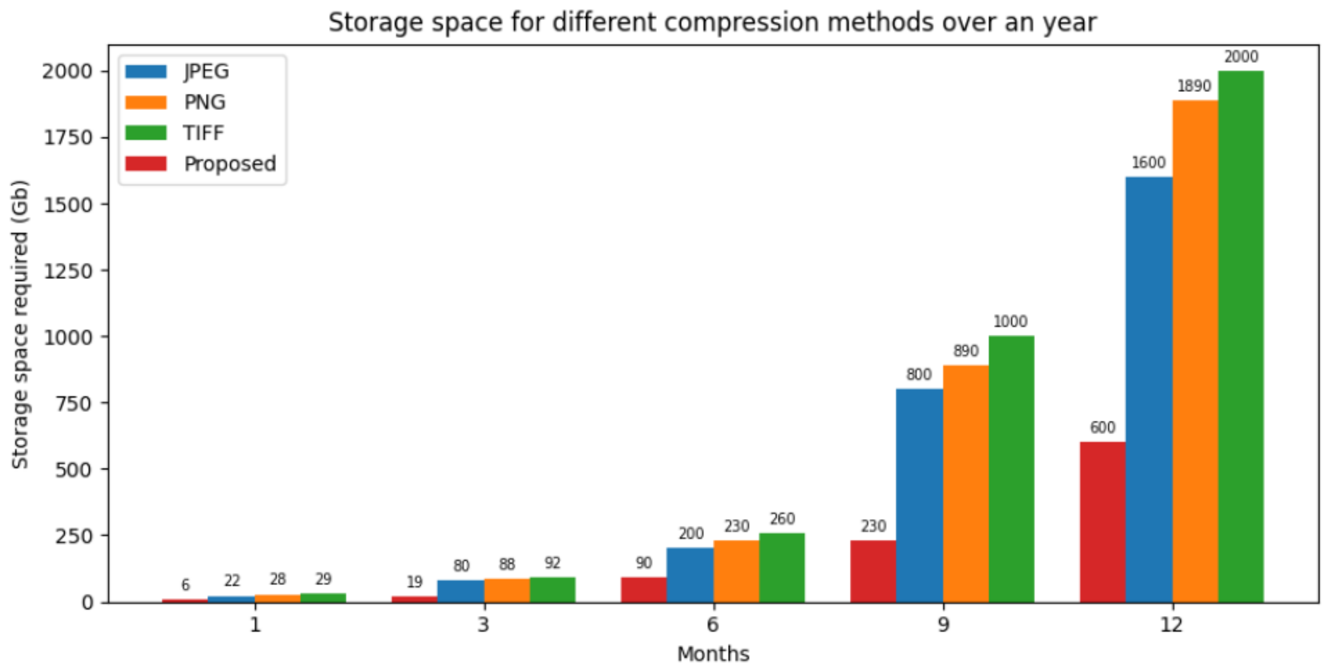

Figure 12

Storage space requirements of different algorithms for 12 months

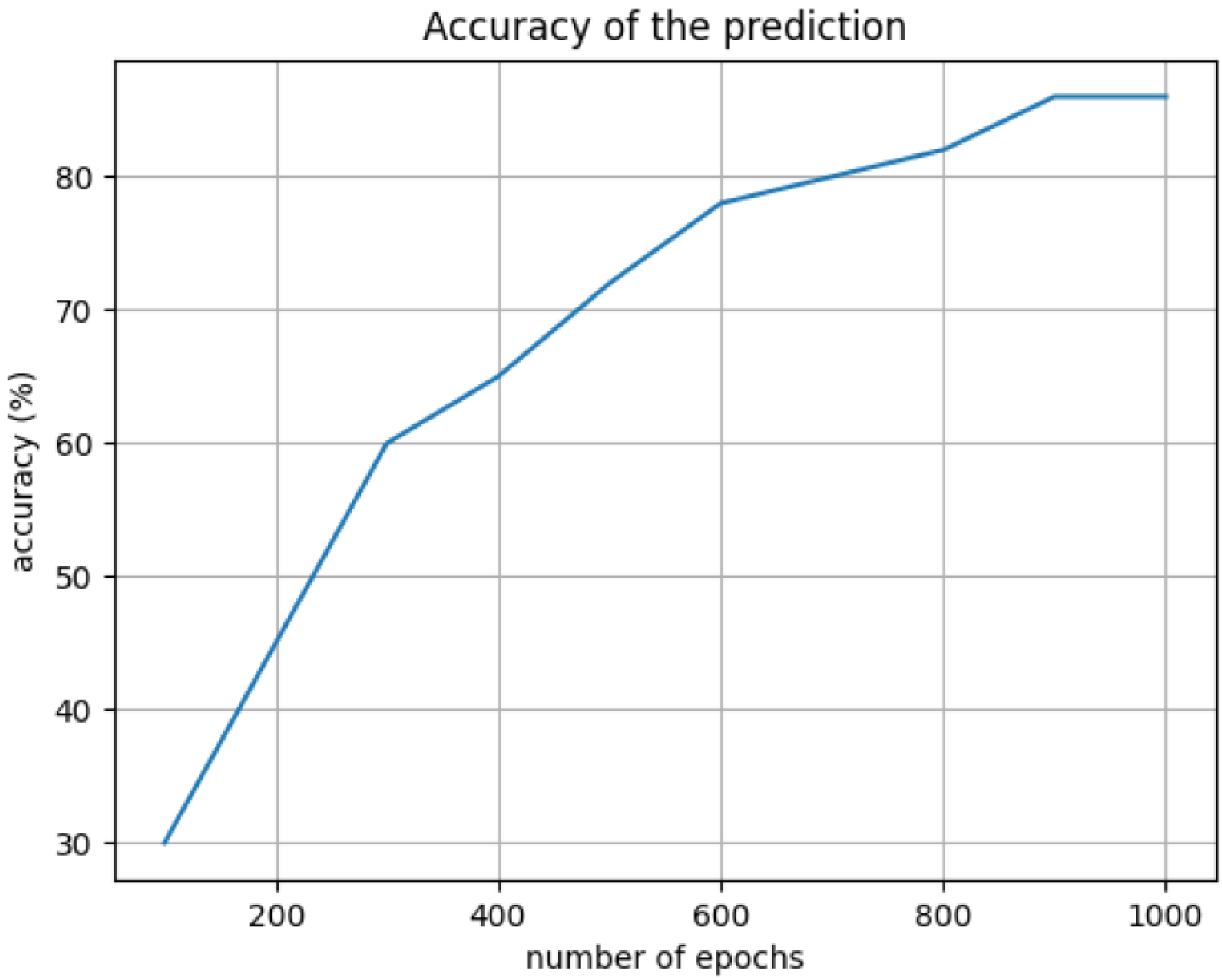

Figure 13

Effect of epochs used in training phase and accuracy of the prediction

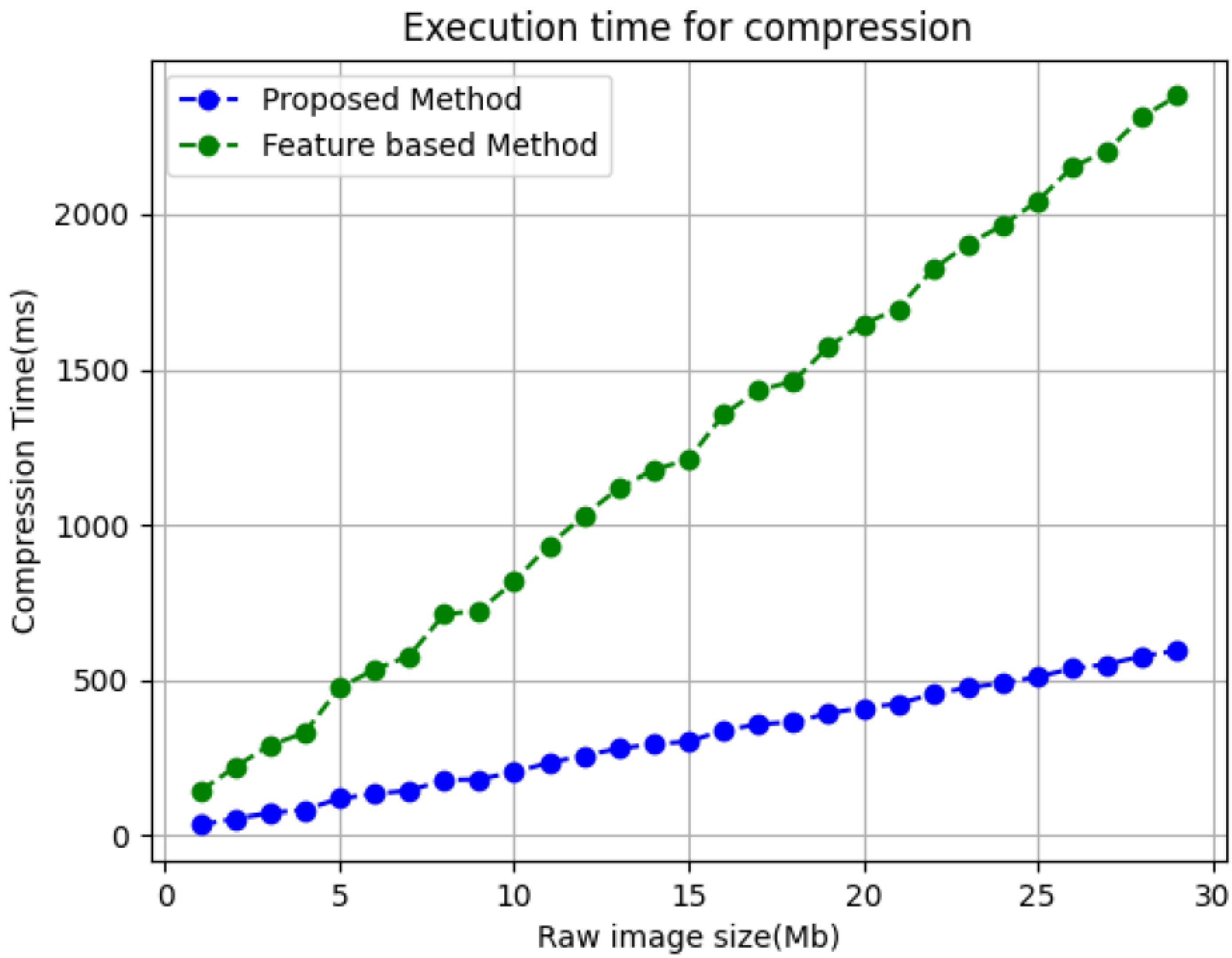

Figure 14

Encoding time taken by feature based & proposed method for various image sizes