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Research Article

Map Reduce Based Endoscopic Video Compression and Artificial Intelligent Video Splitter Approach for Lossless Video

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ABSTRACT

Endoscopic video storage is a major issue today in cloud-based health centre. The Electronics Health Record must include full-length endoscopic surgeries for diagnosis and research. Hence this is paper presents compression of endoscopic using Map Reduce technique. Artificial Intelligent based solution is employed as an intelligent video splitter to form the key value as "Map" stages to filter the endoscopic video into a group of frames based on redundancy. These outputs are passed to "reduce" to merge them into a single output. After mapping and reducing endoscopic video frames, lossless compression is applied and the experimental results for PSNR 30-40 dB, SSI 0.7-0.8, Bitrate 32.17 and MSE 2.1 is obtained.

Keywords: Hadoop, MapReduce, HEVC, PSNR, MS-SSIM, bitrate, Compression Ratio GOP.

1. INTRODUCTION

Video cloud services for hospitals are just one example of the rapidly expanding market for e-Health and telemedicine-related products and services. National health care policy is gradually recognising telemedicine services, which use videoconferencing or other ICT technologies to enable distant treatment and consultations, as valid treatment choices. Countries including Germany, France, and Poland no longer mandate in-person patient-doctor meetings as of 2018 [1]. Even while similar offerings have been on the market for some time in the United States, European companies that want a piece of the pie will need to provide solutions that comply with European legislation and account for the wide variety of healthcare systems in Europe. The telemedicine industry is growing [2]. As video technology advance, the amount of space required to store medical footage grows. Now that Full HD systems are the standard and 4k and 8k resolution systems are on the way, this is more important than ever. High quality surgical stereoscopic video is based on two streams of 1.5 Gbits/s each, while radiological images from a CT scan, MRI, or PET scan might take up several hundred megabytes per test. In 2009, 2.5 PBytes were needed to store mammograms in the United States, and by 2010, 30% of all photos kept globally were medical images [3]. Medical records are kept for extended periods in many nations. Medical photographs of patients must be stored for 20 years in Poland and France. It stores photos and video. 2015 France created 55 TBytes of picture data. Two hours of footage can be recorded on a full HD endoscopic camera used in endoscopic surgery. These figures highlight the difficulty of

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storing historical records. So, for regular use by health specialists, medical images and videos should be encoded (compressed) if doing so does not compromise the therapeutic quality of the material. It is vital that the compression phase of the encoder does not result in significant loss (degradation) or additional processing, such as watermarking, whether the data is being transmitted or stored. As a result, high-quality video is essential for medical professionals. Select codes that require less room for filing while still protecting patient safety. Compressing medical data is essential now. Consider the hospital's storage requirements. On a daily basis, endoscopic procedures account for 3% of the 32 operations performed in hospitals [5]. To meet the demands of developing applications like UHD TV in 4K and 8K resolutions, 360° video, and higher quality formats like HDR, HFR, and WCG, a new generation of video codecs is being created. Next-generation video codecs include VoD applications use AV1. Open and royalty-free AV1 codec. 2017 studies found that AV1 reduces bitrate by 17%-22% compared to H.265/HEVC [4]. ITU-T VCEG and ISO/IEC MPEG formed the Joint Video Exploration Team on Future Video Coding (JVET) in October 2015 to determine if a new codec with compression capabilities beyond HEVC is needed. HD, UHD, HDR, and 360° films have been tested, and advanced compression algorithms have been investigated utilising a shared software platform [5]. JVET hopes to finish a new codec standard by 2020 (ITU-T may call it H.266). The open-source x265 encoder (which inherited its core techniques from x264 H.264/AVC) and commercial HEVC/H.265 encoders are available. We believe that only strict compression should be considered when dealing with the massive volumes of data that would be generated by recording medical operations. Therefore, it is essential that the quality for medical applications be considered during the standardisation of new robust compression codecs. Multiple journals have reported their findings on compressing medical videos for long-term storage. However, it's important to note that studies on multimedia data compression in medicine are typically conducted in highly specialised areas of medicine.

However, as the demand for high-quality video content continues to grow, there is a pressing need to explore new and more advanced compression techniques that can further enhance video quality while reducing file size even further. With the increasing availability of high-resolution video content, the need for efficient compression techniques will only continue to grow. Although we are primarily interested in video compression at the moment, we do discuss the storage implications of other data types utilised in the development of endoscopy system, such as electronic medical records, patient registries, and patient-generated data and videos. [6].

2. RELATED WORK

The growing dimensions of data quantities generated by different medical imaging modalities and the increasing prevalence of medical imaging in clinical practise necessitate data compression for the distribution, storage, and management of digital medical image data sets. Since the advent of new technologies like the cloud, telemedicine, DICOM, and PACS (Picture Archiving and Communication Systems), data compression has become crucial. According to research by S. Ponlatha et al. (2013), advances in medical imaging have hastened the accumulation of photographic evidence. Large and efficient storage systems are needed to house the enormous medical datasets produced by positron emission tomography, magnetic resonance imaging, computed tomography (CT), and single-photon emission tomography. Therefore, compression is an essential part of medical imaging, as it shortens the time it takes to send massive image studies like high-resolution three-dimensional CT datasets and reduces the amount of space they take up in storage. Video compression algorithms have inter-frame redundancies; however, these are not used in current medical picture compression standards. New DICOM WG-4 compression JPEG2000 is an add-on to JPEG. The compression of medical images allows for a lower bit rate, more space in storage, and a faster video quality. The improved quantization matrix used by JPEG2000 is called a genetically designed GQM. Input blocks are used to quantize feature-based matrices. Here, compression is driven by the application. It is necessary to have a fitness function. Medical applications rely heavily on visual perception . N. Senthilkumaran et al. (2011) put forth a proposal for lossless image compression. The system demonstrates that the improved Backpropagation Neural Network Technique is superior than Huffman Coding for lossless image compression by comparing X-Ray images on the basis of compression ratio, transmission time, and compression performance. Moustafa M. Nasralla et al (2018) examined the quality of medical video encoded with HEVC and H.264/AVC. The JCT-VC group compares their findings among intra, low-delay, and random-access settings. In order to provide an accurate comparison, H.264/AVC is set up to roughly mimic the setup settings of HEVC. Using 4G network simulations, we compare the system resource utilisation in user authentication, message, data secrecy, and compression when transmitting HEVC and H.264

encoded videos. S P Raja et al. (2019) suggest compression and authentication for multimedia data due to its large storage needs. Multimedia cannot function without data compression. Cloud-based meta-data businesses can reap the benefits of compression technologies in a dependable manner. The purpose of DICOM is to lay a new groundwork for multiscale transforms and encoding methods. Medical picture compression in the cloud with public-key encryption is a step towards increased safety. Some examples of transformations are the bandelet, contourlet, wavelet, and ridge let. Methods like the Rivest-Shamir-Adleman (RSA) and the Wavelet Difference Reduction (WDR) and the Adaptively Scanned WDR and the Tree Zero Tree Algorithm and the Transmission Efficiency Algorithm are included. Better compression than H.264/AVC means less bandwidth is needed to transmit an HD video over an LTE/LTE network [10]. Since there is such a large quantity of medical photos to save and transmit, a powerful compression method is necessary, as pointed out by Mohamed Uvaze Ahamed Ayoobkhan et al. (2018). Compression methods used in medical imaging must preserve image and video quality. The integrity of medical images is safeguarded via predictive image coding. Restoring medical picture quality, predictive image coding does so by encoding without losing the diagnostically relevant region (DIR). The image is segmented using a graph-based segmentation method, which separates DIR and non-DIR regions. Two feed-forward neural networks (FF-NNs) are used in the prediction method, one for compression and one for decompression [11]. Medical image data mining, virtual reality medical visualisations, and neuroimaging are only some of the areas that Thomas M. Deserno et al. (201l) investigate in terms of the challenges posed by data sets ranging from a few hundred kilobits to several terabytes. As data volumes increase, improvements in image processing and visualisation will be required. GPU-based parallelization and scalable approaches have been created. It is a synopsis of their paper. Such approaches are currently able to deal with data at the terabyte level, but the petabyte threshold is rapidly approaching. Consequently, studies including medical image processing are essential. These days, people are more interested in telemedicine, which uses the internet to link people in far-flung areas with doctors who specialise in their condition. Medical image transmission via telemedicine necessitates large amounts of data storage and network throughput. Compressing medical photos is necessary for both archiving and sending [12]. A sparse representation medical picture compression method based on the geometry of the underlying image structure is provided by S Juliet et al. (2015). Regular variations in greyscale are shown by the geometric flow of an image. Important coefficients can be lowered in the decomposition of wavelets via geometric regularisation. When medical images are compressed and an optimal storage and communication solution is developed, vital image data is preserved and processing errors are avoided. MAE, UIQ, and PSNR all have a role in getting there [13]. Scholars and professionals alike are interested in cloud video big data analytics, according to a study by Aftab Alam et al. (2020). An efficient video big data analytics platform is necessary because of developments in technology and in business. The current literature does not go far enough in providing an architecture for cloud-based video big data analytics, which would address issues with and opportunities for handling and analysing such data [14]. For better compression efficiency than its predecessor, H.264/AVC, HEVC (High Efficiency Video Coding, or H.265) was developed as a video compression standard. HEVC is able to accomplish its goal of compressing video without sacrificing quality by making use of a number of cutting-edge techniques [15].

Building upon the findings of the existing literature, still there is need to address compression the of data in the medical field which can be done by utilizing the inherent technology such as cloud. Which serve as one of the major resource providers. Cloud is being used in the medical field such as secure storage and backup, Collaboration and sharing and remote access. So, among this storage is major issue. Specifically, we aim to compress the endoscopic video using Map Reduce technique. By doing so, we hope to contribute to the development of novel compression technique for the endoscopic videos in cloud-based health centre.

While there is still much to be learned about compression, the research work will help to advance the field Hadoop framework, artificial intelligence and machine learning which provides a valuable insight cloud and artificial intelligent based techniques.

3. PROPOSED ARTIFICIAL INTELLIGENT BASED VIDEO SPLITTERS FOR ENDOSCOPY VIDEOS.

For experiment purposes, the Endoscopic videos from the database table 1 range in size from 77.41 MB to 31.25 MB is considered for experiment purpose. These videos are divided into group of pictures using an Artificial Intelligent (AI) based splitter. An AI-based video splitter can work in parallel environment by employing a distributed parallel

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programming approach, in which video frame processing is divided across numerous computing nodes. For the experimental results, it is deployed in the stand-alone machine. The pseudo code for the AI based video Splitter

Step 1. Load the video file from the Cloud or from Memory of standalone.

Step 2. Set a similarity index threshold value.

Step 3. Set the frame size to 15

Sept 4. Get the total number of frames from the video.

Step 5. Divide the total number of frames by the frame size to get the total number of groups

Step 6. for each group

a. Initialize a variable to hold the average similarity index (Th).
b. For each frame in the group:

i) Extract the frame

ii. Apply any necessary pre-processing (e.g. resizing, color normalization)

iii. Run the frame through a similarity index algorithm to get the similarity index

iv. Add the similarity index to the running average

c. Calculate the average similarity index for the group by dividing the running average by the number of frames in the group

d. If the average similarity index is less than the threshold value:

Remove the frame and reset the running average to 0.

else add the frame

e. If the group is the last group:

i. Output the group as a separate video file

Step 7: End

Figure 1: shows the AI based video Splitter workflow. The threshold value obtained is the range of 8- 9.

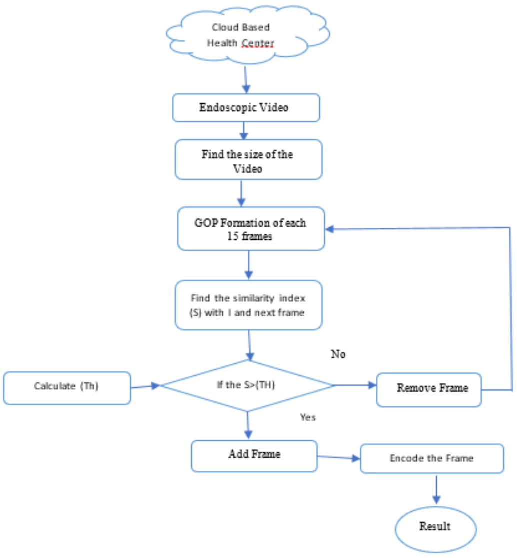

Fig 1: Proposed of AI-based Video Splitter for endoscopic Videos.

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Table 1: Database of Endoscopic Videos

Video	Memory (MB)	Time	Bytes	Frame Height	Frame Width	Frame Rate/Sec	Bitrate
1	77.5	19:15	######	320	240	30	445kbps
2	65.8	09:30	######	320	240	30	831kbps
3	65.4	######	######	320	240	30	295kbps
4	40.6	6.52	######	320	240	30	688kbps
5	35.9	05:52	######	320	240	30	713kbps
6	26.5	04:24	######	320	240	30	697kbps
7	25.7	04:22	######	320	240	30	687kbps
8	25.6	06:30	######	320	240	30	492kbps
9	20	03:18	######	320	240	30	705kbps
10	18.4	03:02	######	320	240	30	692kbps
11	15.9	05:36	######	320	240	30	337kbps
12	14.8	05:03	######	320	240	30	569kbps
13	13.3	04:13	######	320	240	30	367kbps
14	11.7	02:00	######	320	240	30	684kbps
15	6.44	01:30	######	320	240	30	500kbps
16	5.86	01:01	######	320	240	30	673kbps
17	4.59	00:53	######	320	240	30	611kbps
18	4.47	01:47	######	320	240	30	307kbps
19	3.12	00:52	######	320	240	30	415knps
20	2.97	00:37	######	320	240	30	566kbps

4. PROPOSED METHODOLOGY FOR COMPRESSION OF ENDOSCOPIC VIDEO USING MAPREDUCE TECHNIQUE

Cloud-based health centres struggle with massive medical data collections. Large volumes provide a problem for storage and communication. The resolution, frame rate, compression method, and duration of an endoscopic video determine its storage space. Endoscopic videos are usually 720p or 1080p and 30 fps or it might be less depending on the size of the video. The video may last a few minutes or several hours, depending on the diagnosis. The following formula estimates the storage space needed for an endoscopic video recorded at 1080p, 30 fps, for H.264 or H.265 compression.

Storage space = (bit rate x duration) / 8, where bit rate is the data per second needed to encode the video and duration is its length in seconds.

For example, if the video's bit rate is 5 Mbps and its runtime is 60 minutes (or 3,600 seconds),

Then the storage space needed is:(2.25 GB) = (5 Mbps x 3,600 seconds)/8

Thus, a 60-minute endoscopic film compressed with H.264 or H.265 at 1080p and 30 fps would take 2.25 GB of storage. This is merely an estimate and may vary depending on video characteristics. Now Depending on the size, the videos are divided using Proposed AI based splitter. The result obtained is GOP, so these are then assigned to the Master node in case of Cloud based health care centre and processor does the similar task in the standalone system. MapReduce based compression is implemented in MATLAB and video compression technique worked well in experimental results. The generates GOP from AI based video Splitter is mapped and reduced by Hadoop uses MapReduce. The MapReduce Parallel Paradigm first converts the frame to turn one set of "Key, the value"-formatted input data into a distinct set of output data using predetermined mapping rules.

4.1 Novel Hadoop based MapReduce video encoding technique

Step 1: Map Operation ()

1.1 Get Started with Map Operation (Key, Value) // key: Video Title, Value: Video Title and body Call

1.2 Call **Intelligent Video Splitter** (key, value)

for *each block in* **Nf**

1.2.1 transcode Intermediate (s, "format");

end for

end.

Step 2: Video Reduce Operation ( )

2.1 begin to Reduce (String key, Iterator values) // key: a cut, values: a list of Transcoded BlocksTNf

Video v1;

for *each v1 in* **Transcoded Blocks TN f**

Emit (AsMergedVideo(v1));

Store it in Cloud Video Database

end for

end.

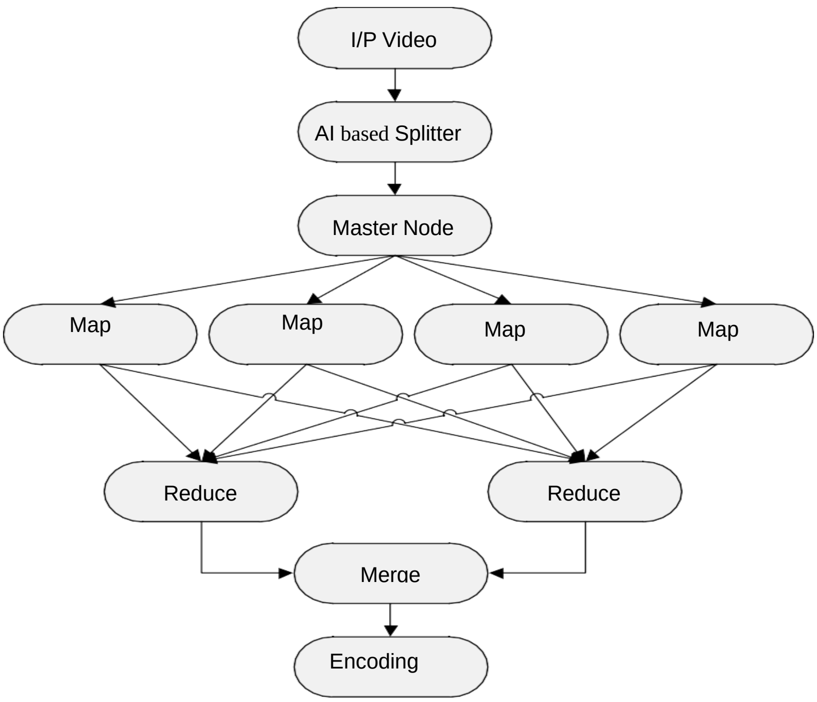

Fig 2: Block Diagram MapReduce video transcoding

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We begin by dividing the video into 15 single-frame GOP chunks using a sophisticated video splitter. As can be seen in Fig 4, the HDFS name node is responsible for allocating GOP blocks to the appropriate heterogeneous data node. The map phase data node converts data blocks from Nearer GOP into the necessary video format. After all the portions have been transcoded, they are concatenated to make the final video.

5 RESULTS AND DISCUSSION

The experimental configuration is setup in the MATLAB on single machine, AVI video compression is supported by MathWorks' MATLAB. For reading and writing AVI files, as well as processing and compressing video data, MATLAB includes built-in functions and tools. The standalone machine with 16 GB RAM and i7 processor is used for experimental study of results. These standalone machines have 4 cores which can be as threads or worker for dividing into the smaller chinks. The one core is designated as the "master" node for distributing the workload for compression and the remaining cores are used for load sharing for the compression of the endoscopic video data. The work can be migrated from the standalone to the cloud environment in

Hadoop framework, so the Map Reduce compression technique is also be migrated to the cloud-based application.

In this part, we present the outcomes of our experiments with the suggested Hadoop-based Endoscopic video compression. The Proposed system primary focus is on successfully compressing input videos by transforming them into a series of GOP frames. Information regarding how the endoscopic footage was mapped and compressed is shown in Figure 1 and figure 2. The effectiveness of a MapReduce task processing a huge video can be greatly affected by the number of mappers and reducers utilised. More mappers and reducers are needed for processing larger videos because each mapper and reducer must process a smaller portion of the video. The Figure 5 shows the first original frame of endoscopic image after applying the MapReduce to endoscopic video before compression and HEVC final inter frame. Figure 3 shows the final compressed progresses of an endoscopic video of a typical endoscopic video. The experiment results are obtained by considering the 5 endoscopic videos for compression and consider the parameter for study purpose as shown in the table 1. Figure 4 shows the graph of Inter code encoding bitrate. The original bit rate of the sample video 2 is 445 kbps and the obtained bit rate 32.03 kbps.

Bit rate Reduction Percentage = (1 - (Compressed Video Bitrate / Original Video Bitrate)) x 100 Bit rate Reduction Percentage = (1 - (32.47 kbps / 445 kbps)) x 100

Bitrate Reduction Percentage = 92.7%, bitrate may vary depending on the specific requirements of application and video. While a bit rate reduction percentage of 92.7% is significant and indicates that the compression technique is effective, the ideal number is dependent on the unique requirements and limits of the compression environment and the application context. In general, a PSNR value of 30 dB or higher is considered to be of high quality, while a value of 20-30 dB is considered to be of medium quality, and a value below 20 dB is considered to be of low quality in the figure 6 shows the achieved PSNR values of 5 endoscopic video of average value 36.19 dB, which is an ideal for present application. While a PSNR value of 36.19 dB is regarded enough for streaming videos over the internet. Lower MSE is better, as it indicates a smaller difference between the original and compressed video frames in figure 10 shows the graphs for MSE.

Using the following formula, the Peak Signal-to-Noise Ratio (PSNR) can be derived from the Mean Squared Error (MSE):

PSNR = 10 log10((MAX2)/MSE) where:

• MAX: the video's maximum pixel value (for example, 255 for an 8-bit video).

• MSE: the mean squared error value calculated from the compressed and original videos.

The PSNR value is the proportion of the maximum pixel value to the root mean squared error (RMSE), which is the square root of the MSE.

The maximum pixel value of a video is 255 and the MSE value obtained from the compressed video and the original video is 2.4. The PSNR can be determined using the algorithm above as follows:

PSNR = 10 log10((2552) / 2.4) = 36.19 decibels

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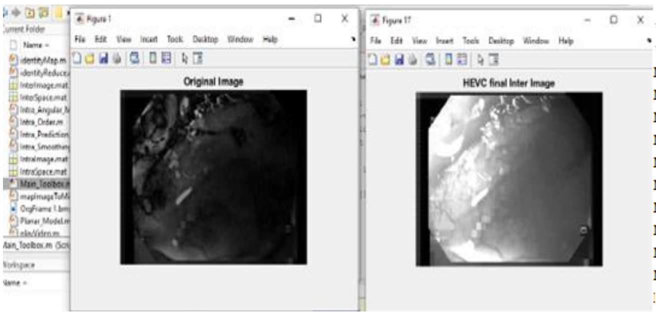
As a result, the PSNR for this compressed video is 36.19 dB. As a result, the MSE and PSNR values obtained matches.

The ideal SSIM for compression of video depends on the specific requirements and the type of video content being compressed here we achieve the average value of 0.83 graph in figure 9 shows. The compression ratio of 0.45 means that the compressed video is 45% the size of the original uncompressed video, indicating that the compression level is relatively high. It should be noted, however, that higher compression ratios can result in worse visual quality and fidelity's important to note that no one parameter can be used to justify the measure of video quality, and should be used in conjunction with other measures, such as PSNR (Peak Signal-to-Noise Ratio), MSE (Mean Squared Error), SSIM and subjective testing, to determine the optimal compression settings for particular video application.



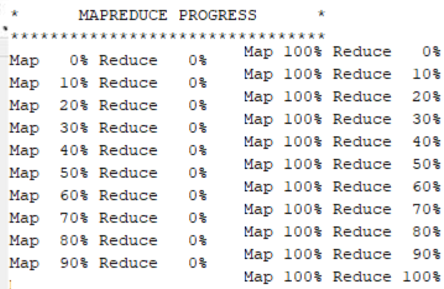


Fig 3: Original image and final inter frame. **Fig 4**: Map Reduces Progress of Endoscopic video

Sample Video	Bit Rate	PSNR (dB)	MSE	SSIM	C-R
1	31.91	37.07	2.02	0.9	0.45
2	32.03	35.72	2.75	0.8	0.45
3	32.97	35.44	2.71	0.86	0.44
4	32.23	35.79	2.94	0.84	0.45
5	32.49	36.95	2.07	0.8	0.45

Table 2: Results of 5 Endoscopic Videos

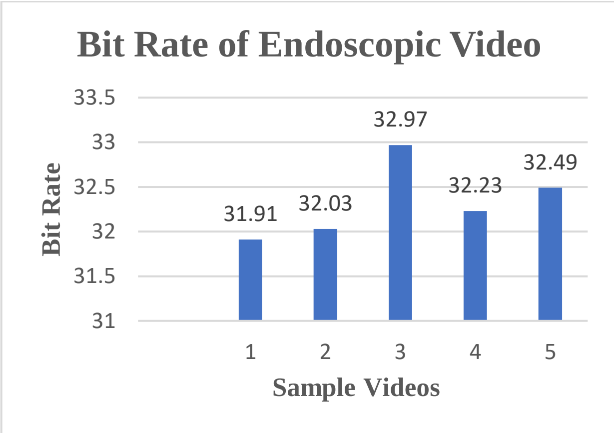


Fig 5: Inter encoded bit rate of Endoscopic Videos

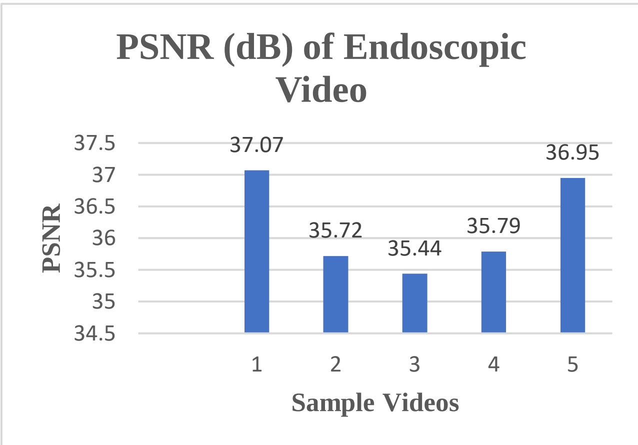


Fig 6: PSNR Value of Endoscopic Videos

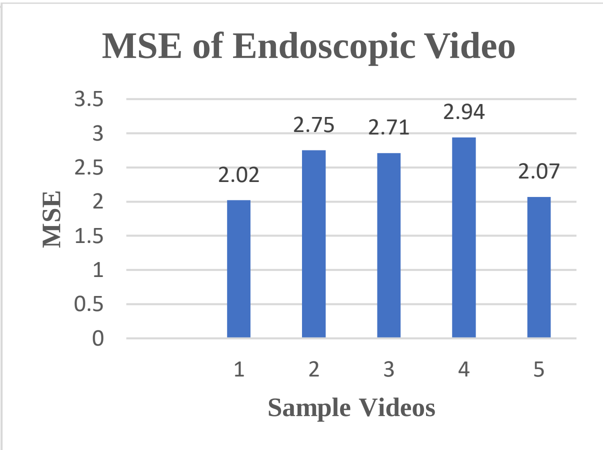


Fig 7: MSE value of Endoscopic Videos

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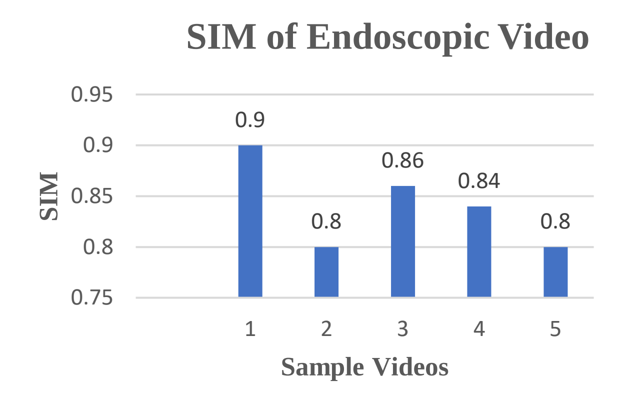

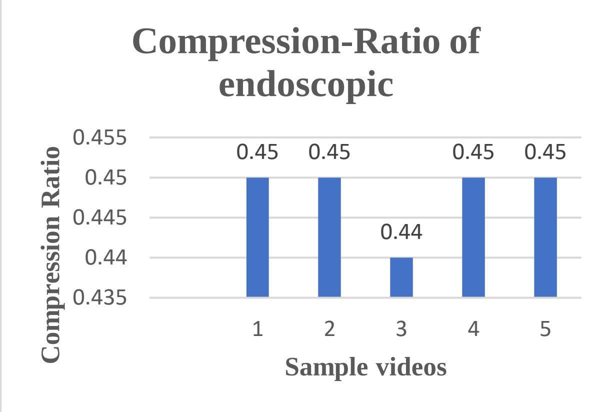

Fig 8: SSIM of Endoscopic Videos **Fig 9: Compression ratio of Endoscopic Videos**

CONCLUSION

The proposed MapReduce based compression technique solve the storage problem of endoscopic videos in a large-scale private cloud as health-based cloud centre. Which uses an AI-based approach to split the video frames into groups based on redundancy, which are then processed using the MapReduce framework to produce a single output. The output frames are later compressed using a lossless compression technique to reduce the storage requirement while maintaining identical quality and bitrate of the original video. The compression results achieved on average PSNR of 36.19 dB, SSIM of 0.8, MSE of 2.4, and a bit rate of 32.94 The proposed technique has shown promising results and can be used to efficiently compress and store endoscopic videos for further diagnosis and research.

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