International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 5, 2025
https://theaspd.com/index.php

Hybrid Quad-Tree And Nested Multi-Type Tree-Based AI Techniques For Video Compression And Transmission In 5G Applications

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Abstract:
Back ground: *The emergence of 5G networks has resulted in a revolution in real-time video applications, necessitating effective video compression and transmission solutions that can fulfill high bandwidth, low latency, and improved quality requirements.*
Method: *The present paper develo ps a hybrid solution as a mesh of Quad-Tree and Nested Multi-Type Tree algorithms and implementation of Artificial Intelligence (AI) to enh a nce the video compression and transmission efficiency under 5G circumstances. The model employs a hierarchical format of quad-trees to spatially compress and multi-type trees to deal with vary video qualities to enhance the most effective resource usage. The dynamic modification of compression parameters is done by machine learning approaches leading to enhancement of rate distortion and reduction of computing overhead. The paper shows that the AI-based algebraic hybrid-tree approaches can be a robust basis of video services of the next generation in 5G.*
Results: *The proposed solution overcomes the limitations of existing encoding systems such as JPEG, MPEG, AVC, and HEVC by delivering better compression rates while maintaining video quality. Experimental results reveal significant improvements in compression efficiency, transmission reliability, and overall video quality as compared to older methods.*
Conclusion: *The AI-assisted hybrid-tree-based method would enhance the video compression and transmission of 5G networks to a considerable extent. This performs better than the traditional method where there is optimization in rate-distortion and also on the load. This sorted method provides a favorable platform of next-generation real-time video exploitation.*
Keywords: *5G Networks, Artificial Intelligence (AI), Machine Learning, Quad Tree with Nested Multi-type encoding, MPEG.*

I. INTRODUCTION:

Artificial intelligence (AI) is a vital component in enhancing video compression through dynamic parameter modification based on video content. Machine learning approaches reduce processing costs and allow the system to anticipate and react to changing video by automating the process of selecting the best encoding strategies. AI-driven approaches that use continuous learning can improve rate distortion performance and enable real-time, resource-efficient video transmission on 5G networks. The rapid progress of 5G networks has created new opportunities and challenges in the realm of video compression and transmission. 5G's promise of ultra-fast internet speeds, low latency, and widespread device connectivity makes it perfect for applications such as high-definition video streaming, virtual reality (VR), augmented reality (AR), and telemedicine. However, the massive demand for high-quality video content in real time, along with limited bandwidth resources, mandates the development of effective video compression algorithms that can balance compression rate, video quality, and transmission efficiency.

Video consumes most of the data on Internet but it is possible to reduce the load consumed by the access demands on the bandwidth consumed by the films to ensure that the users access the video information in a quick way. 5G Technology is among the most significant futures of mobile broadband that develops exceptionally fast in terms of mobile communication[1]. It is also one of the finest conversions of the services offered by mobile network operators in to communication service providers. Technogly 5G is advanced by mobile broad band (e-MBB), ultra low latency communication and machine type communication[2]. Internet has been growing at a very explosive rate all over the world and the size of data in the internet is proving to be a big challenge. The major technical needs of 5G networks (according to 5GPPP) are: As compared to previous networks, 5G networks are low latency, high data rate and mobility to make easy transmission, storage to transmit high quality video data(HD to UHD). The key use-cases of the 5G networks as proposed videos include Live video telecasts, interactive and real time video conferences and other VoDs[3]. Compared to current encoders, this architecture allows low bandwidth usage, and also it works in harmony with the 5G network in terms of its transmission speed and latency. High-speed 5G with low latency is more desirable with better methods of compression. Other video compression formats that have been widely used, to compress video, are JPEG, MPEG, AVC (H.264) and HEVC (H.265). These solutions often cannot hit the balance just right between the compression and video quality, especially where scenarios require high resolution video and low latency. Consequently, the need to use video format in different applications is on the increase.

Applications	**Bit Rate (Kpbs)**	**Video Standards**
DVD video	6000-8 000	MPEG-2, AVC/H.264
Internet	20-200	MPEG-4, AVC/H.264, H.263
Telephone and conference	20-320	MPEG-2, AVC/H.264
TV Broad Casting	2000-20000	MPEG-2, AVC/H.264
Video over 5G wireless networks	20-200	MPEG-2/H.262, AVC/H.264, HEVC/H.265

Video compression refers to technique of decreasing the size of a video file or picture taking advantage of both spatial and temporal redundancy within and across a number of frames of the video. A successful video compression system aims finally at reduced data volume, but at preservation of perceptual quality of the material decompressed. Video and image data Compression Compression is a process by which the number of data required to represent the input signal is reduced to a certain level in order to improve efficiency in storage and transmission. Compression can be the result of the reduction of the redundancies of space, time, statistics and psychovisual redundancies that exist in pictures and videos [4]. The picture and video compression segment has developed rapidly in the recent years and a number of coding solutions have been developed and research has been undertaken on them. The development of the image and video coding applications has been accelerated by developing international compression standards[5]. A number of still image compression standards such as JPEG and JPEG 2000 are employed in the RGB colour impage compression procedure of various commercial and medical applications[6][7]. Similar lossy or lossless methods were also needed in compression standards of videos in video compression of frames.

From Fig1. A Digital video system is made up of the encoder and the decoder which are usually two distinct components. Through encoding, one of the video qualities is maintained. Video reconstruction Decoder in video reconstruction a the decoder who codes information in the compressed video channel will utilize that information to reconstruct video explaining the quality of the video. In order to produce the high-quality video, preserving the good compression ratio, a powerful encoder might employ more effective tricks and compound algorithms. On the whole, they are observable in the form of the video conferencing system. This paper suggests a methodology in which Quad-Tree and Nested Multi-Type Tree data structure along with Artificial Intelligence (AI) strategies of compressing and transmitting video data are used effectively.

Nested Multi-Type Trees are the combination with the commonly known Quad-Tree type that is characterized by the spatial partitioning capabilities which can also signify various hierarchical data structures. These trees are optimized through the machine learning techniques, and they become adaptive to different types of video data and compression requirements, which brings a significant compression performance improvement in the video without the considerable deterioration in the video quality.

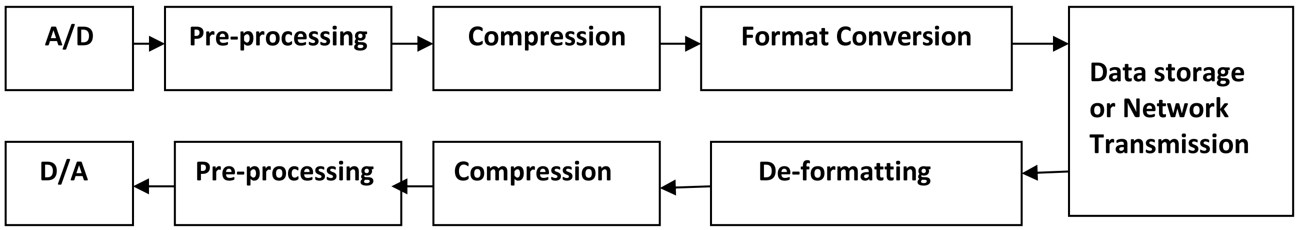

Fig1. Block Diagram for digital video system

II. Video Compression Standards

Video compression highly depends on motion image frame inter-coding. Local and global motion estimation is coupled in this research with block matching techniques of local motion estimation and sprite coding as applied to the compression of motion picture frames. Many studies indicated that combining local motion estimates with global motion estimates significantly yielded more quality photographs in the real estate market and reduced the search time to obtain appropriate matching. Consequently, the method offers low bit rates to compress the video. The grouping of greater number of sequences of frames form the video, which has very less differences between adjacent or sequences of frames. 3 different types of frames are assumed in the operation of video processing and those frames are called Information frame or key frame, Predicted frame and Bidirectional frame. There is more information in the informative frames[8]. The processing of this same is the same as the image processing. The p-frames are beneficial in the video reconstruction using the assistance of either of the forward or backward frames. The B-directional frame operation also closely relates to p-frames but contrary to p-frames instead of one direction it has a bilateral operation. Difference between two neighboring or consecutive frames may be stored which is useful in reconstituting the original video signal at receive or output point. I, P and B frames can perform Intra and interceding operations in General compression operations. The I-frame can perform its intra-coding operations whereas the p- frames and B- frames can perform the inter-coding operations. The quality and the ratio of the compressed video also constitute the manner of the operations of a certain type of a frame. I-frames are of quality (and size) and B-frames compress better and have less quality. This space between two I-frames can be regarded as the signifier to the quality of the MPEG video. The above sequence is going to give good quality and compression results since it has been tested so far through practice. Motion compensation algorithm constitutes a very significant component in the video encoding process, precisely in interframe coding within motion estimation algorithm. Motion estimation is a research on pixel motion frame to frame. Such knowledge of object motion is used to accomplish data compression in form of In Motion compensation algorithm preferred pel-recursive algorithm (PRA) and block-matching algorithm (BMA) in motion estimation and motion compensation algorithm. This is employed to generate the references among the different kinds of frames. A motion vector will depict how motion is correlated in two frames. Execution quality of motion estimating algorithm plays a major role in determining the final frame correlation and thus pixel arithmetic difference. The advantages of the proper estimation include higher compression ratios and video quality. Nevertheless, motion estimation is computationally intensive and thus, in many cases, not appropriate to real-time scenarios. The threshold is used to reduce the computation done in motion estimation of frames computation. Block matching is a time-consuming procedure in Video process. During this, the existing frame is matched with the previous one in a search area in order to find a matched block.

III. Motivation of the Research:

As the world implements 5G rapidly, real time video applications that require high definition in broadcast, like remote health and automobile autonomy, live video streaming, and virtual reality, is in strong demand. Video compression techniques that can handle such huge volumes of data and also, operate within the strict demands of 5G that include high bandwidth, low latency and also, high video quality are necessary to these applications. More modern, well-established encoding technologies, such as JPEG, MPEG, AVC and HEVC, which used to be perfectly fine previously, simply cannot possibly be adequate to these high requirements. Therefore the next-generation video compression model should be much smarter, and adaptive to support a variety of requirements and conditions in the 5G environments which calls for a highly intelligent model that can adapt its behavior to meet the demands of the environments dynamically.

3.1 Problem Statement:

The current video compression standards have difficulty in balancing between quality, compression ratio and computing power, particularly when deploying into heterogeneous network such as 5G. These techniques do not have the adaptability to respond in real-time to alterations in the contents of videos and fluctuations within the network. This causes inefficiencies in form of excess bandwidth, latency or poor video quality. Plan of the whole paper: The key issue that is going to be considered in this paper is to come up with a hybrid, AI-assisted compression and transmission scheme, which is capable of adapting intelligently and optimizing compression parameters, rate- distortion performance and the overall computational overhead- hence, in this manner, the paper should be the smooth streaming and high-quality video-digest that will be well matched to the 5 G enabled real time applications.

IV. Proposed Method

All the frames/pictures of each scene are resized to a standard dimension such as 300 x 300 pixels or 500 x500 pixels.In this procedure, all the frames are brought at one size so as to easily measure the compression rate of all the frames. In most cases, there has been increase in superior video compression algorithms to high-resolution videos with the frequency of consumption of video information. With the approach, the video compression may be through the principal component analysis approach that is based on machine learning. Each frame of the sequence video can get the sequence video frame individual frame variance using the covariance matrix, the eigen values can be calculated based on eigen vectors of each frame[11]. Low and high-frequency component also occurs in the video frames and the low and high frequency component in the video frames are separated in the principal component (PC) frames[12]. Interface coding: The versatile video Coding (VVC) is a video codec that is preferred to interface coding and it is developed to reduce complexity significantly and enhanced efficiency of video coding by The QTMT (quad tree with nested multi-type tree)[13]. Duplicate images within each frame are identified and this is followed by the elimination of the number of similar images and the place count is recorded to enable the duplicate to iterate instead of the duplicate. Information coding requires the use of a quick inter-coding algorithm to identify and make note of the present similar images with the occurrence of an iterated in place of duplicate. The minor modifications are preserved along with motion estimation algorithm GAN and are noted by LSTM and with the aid of these undesired elements or data of the frame are removed and substituted with zeros. The creating part of the video can be carried out in such a way that the duplicate is generated with the newly generated image which is obtained by using a motion estimation algorithm where the newly generated image is used and can be carried out by storing generated images and giving the trigger duration with that count to create the video[14]. The data after compression is applicable and convenient to transmit, and even to store in case of high speed network like TV and other intra and inter communication channels[15]. In the DVC scheme, Junwei Zhou et al. [2019] proposed that the Wyner-Ziv frames are compressed using what they called a distributed arithmetic code (DAC) but in fact distributed arithmetic code (DAC) is another name used in the literature to refer to a distributed version of the classical arithmetic code (DAC). Their scheme also uses a video coder standard to compress the Key frames[16]. The technique is such that Redudendent information Nested in between the frames in video is reduced with the help of compression algorithm proposed by Jr Jain et.al[1981] to implement interframce coding[17]. R.Westwater et.al[1996] adopted XYZ compression algorithm as a part of data reduction where statistical measurement of spatial and spectral information of pixel is taken[18]. G.J.Sullivan et.al[2010] proposed the Calls for proposal (CfP) on video coding that is more effective in video coding than the addition of AVC standard. The technologies used in this technique were an implementation of the HEVC and JCT-VC (Joint Collaborative Team on Video Coding)[19].

: Daoud et.al[2023] compresses the satellite images collected over multiple bands using deep learning technique. In the process the dimensionality reduction technique is utilized to eliminate the redudendent spectral and spatial data[20]. Dharani.etlal [2023] used pixel level operation in order to enrich the details of the spatial information and spectrail values of the local or gloal image which are useful in identy the particular object after the reduction of the original image [22][23].

4.1 : Machine Learning based Quad Tree with Nested Multi-type tree

The QTMT (quad tree with nested multi-type tree) structure is introduced by VVC. It consist of three modules such as Quad-Tree, Binary Tree and Ternary Tree which is shown in fig.1. The versatile video Coding (VVC) segments the area into different sizes to support more flexibility for partition shapes of the Coding Unit (CU)[21].

To analyze the spatial correlation,

$$\Omega = \{CU1\ , CU2\ , CU3\ , CU4\ \} \qquad [1]$$

All neighboring CUs have gives motion and texture information.

The area of spatial correlation can be defined as

$$\widehat{A_{CU0}} = \sum_{i=1}^{4} w_i . A_{CUi} \qquad [2]$$

Where A^{Cui} is the area of the neighbouring CU

W_i: correlation Coefficient

For small CU , the expected area exceeds the existing CU's by a given amount, meaning it can stop splitting in advance,

$$EN_{QT} = \begin{cases} 0, \widehat{A_{CU0}} > m. A_{CU0} \\ 1, \widehat{A_{CU0}} > n. A_{CU0} \end{cases} \qquad [3]$$

The criterion of performing a ternary split can be defined as

$$En_{TT} = \begin{cases} TT_H, if\ BT_H is\ the\ optimal \\ TT_V,\ \ if\ BT\_V\ \ is\ the\ optimal \\ TT_H, TT_V,\ others \end{cases} \qquad [4]$$

In the meantime, if the CU is programmed in intra mode, it means that the CU's motion feature is too complex for motion estimation to work properly.

The motion complexity parameter MC is defined as

$$M_C = \sum_{i=1}^{4} w_i a_i \qquad [5]$$

The categorize MC into three types as

$$\begin{cases} M_C, < \qquad Th_1, simple\ mode \\ Th_1 \le M_C \le Th_2,\ medium\ mode \\ M_C > Th_2, \qquad others \end{cases} \qquad [6]$$

When M_C is high, it indicates that the neighbouring CUs' motion features are complicated, MC is minimal if a CU is operating in simple mode[24].

Peak Signal – to – Noise ratio and MSE (Mean Square Error), Compression Ratio(CR) & Sum of Squared Difference (SSD) this parameter measures the quality ,& similarity of the output freames proposed method.

$$PSNR = 10 * \log \frac{255^2}{MSE} \qquad [7]$$

$$SSIM=\frac{2\sigma_x^2 + C_2}{2\sigma_x^2 + MSE+C_2} \quad [8]$$

Where C_2 : Constant, $\sigma_x{}^2$: Variance

$$CR= \frac{Compressed\ Video\ Size}{Original\ Video\ Size} \quad [9]$$

$$SSD(I, j) = \sum_{k=0}^{N-1}\sum_{l=0}^{N-1}(C(x+k;y+l) - R(x+k+i, y+l+j))^2 \quad [10]$$

IV. RESULTS AND DISCUSSION:

The compare the performance of the suggested algorithm with machine learning-based encoding method in standard test circumstances. The suggested video compression and encoded scheme was experimented using 4 color video data which are sequences within the RGB and YUV color spaces. Videos are extracted and this extracted video is comprised of 7 frames of 320 x 240 resolution according to the frames per second. Other routine methods can be used to compare with the performance evaluation.

Figure shows a block diagram of the proposed video encoding method. The inter and intra-coding techniques .

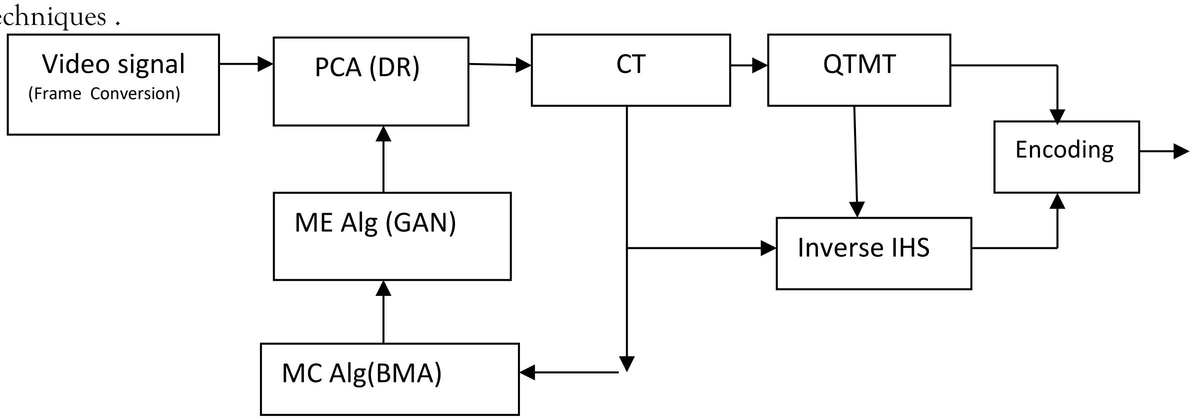

Fig 4.1: Block diagram for Machinle learning based QTMT Method
CVD: Compressed Video Data
ME Alg : Motion Estimation Algorithm
MC Alg: Motioin Compensation Aolgorithm
IHS : Intensity - Hue - Saturation
PCA: Principal Component Analysis

Their suggested approach is to use the most up-to-date deep learning approaches to enhance compression to the point of sacrificing video quality. The exploration of the application of AI-based methods such as reinforcement learning to adaptive compression strategies could lead to the improved efficiency of the bit-rate control. Moreover, actual-time streaming application and videos of better definition could also be used to test the approach and give a useful tip regarding its scalability. It may be a huge breakthrough to expand the technology in offering lossless compression without increasing bit rate substantially. Future efforts might potentially consist of hardware acceleration to improve execution times of large-scale applications. Lastly, performance of the method could be compared to the emerging codecs such as AV1 and VVC.

Table 3: Results Comparison of qualitative performance

DATA	Video Compression technique	PSNR	SSIM	Transfer Rate(bps)	Compression Ratio	Execution Time (sec)	Bit Rate Bits/pixel
Video-1	Video-Codec	24.83	0.656	32	42.76	60	0.66
	DVC-Intra coding	32.36	0.593	36	39.37	52	0.57
	MPEG	28.24	0.694	28	52.45	48	0.71
	H.264	32.34	0.654	39	54.34	57	0.75

(MSVD Data set)	PCA	32.65	0.549	42	72.34	78	0.62
	CNN	30.32	0.793	48	75.45	84	0.54
	Proposed Method	37.34	0.828	53	78.66	40	0.45
Video-2 (YouTube2Text)	Video-Codec	29.03	0.645	39	56.34	83	0.55
	DVC-Intra coding	34.56	0.615	45	64.34	72	0.43
	MPEG	29.43	0.698	46	59.54	84	0.66
	H.264	35.46	0.674	34	63.45	68	0.53
	PCA	27.42	0.593	46	72.34	56	0.56
	CNN	38.32	0.811	48	75.34	88	0.59
	Proposed Method	37.49	0.862	52	77.43	32	0.46
Video-3 (ActivityNet)	Video-Codec	32.98	0.635	43	59.89	72	0.56
	DVC-Intra coding	37.32	0.628	48	62.56	84	0.51
	MPEG	36.78	0.673	52	67.78	83	0.52
	H.264	38.54	0.721	49	65.47	78	0.59
	PCA	32.34	0.732	48	71.36	42	0.48
	CNN	37.43	0.815	51	72.74	49	0.53
	Proposed Method	40.42	0.873	55	78.65	37	0.41
Video-4 (AVA Dataset)	Video-Codec	24.23	0.734	45	61.24	74	0.73
	DVC-Intra coding	22.32	0.638	43	65.85	82	0.66
	MPEG	32.57	0.639	49	64.88	84	0.65
	H.264	36.63	0.713	53	63.72	79	0.69
	PCA	31.89	0.724	49	71.94	87	0.59
	CNN	34.38	0.832	55	69.48	83	0.61
	Proposed Method	39.64	0.854	62	77.73	39	0.55

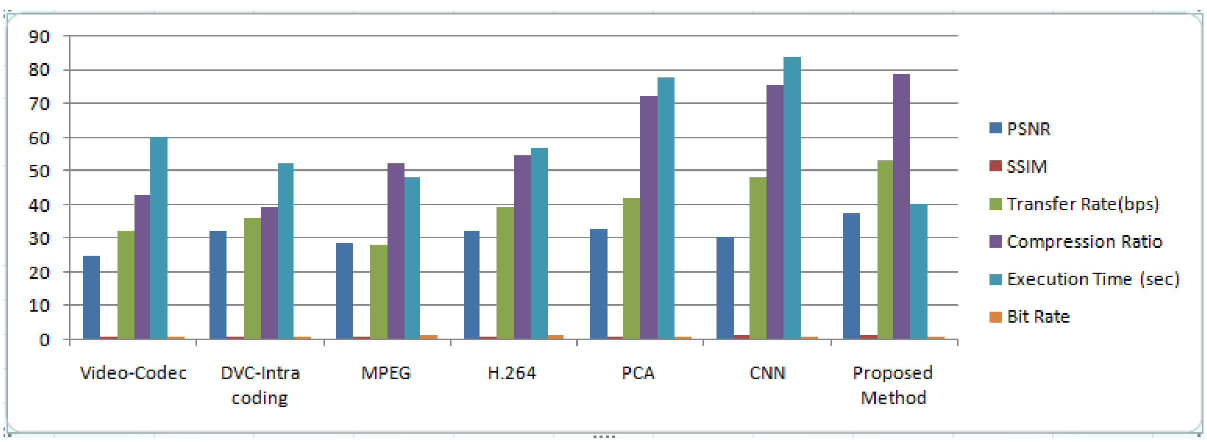

Fig. 4.2: Comparision Results for video -1

Five video data are selected to be the input of the proposed algorithm and the actual data size as well as the compressed data size and the compression ratio are provided in Table 1. The input video data in .mp4 form is of 06 sec and has 15Mb Size. In order to recall the frames randomly with adjacent frames of the sample input video file. The size values of compressed frames will be low in terms of Kilo bites after the procesing of input data. This process is repeated to other video data with different resolutions and size and the same is compared with the required parameters in Table1.

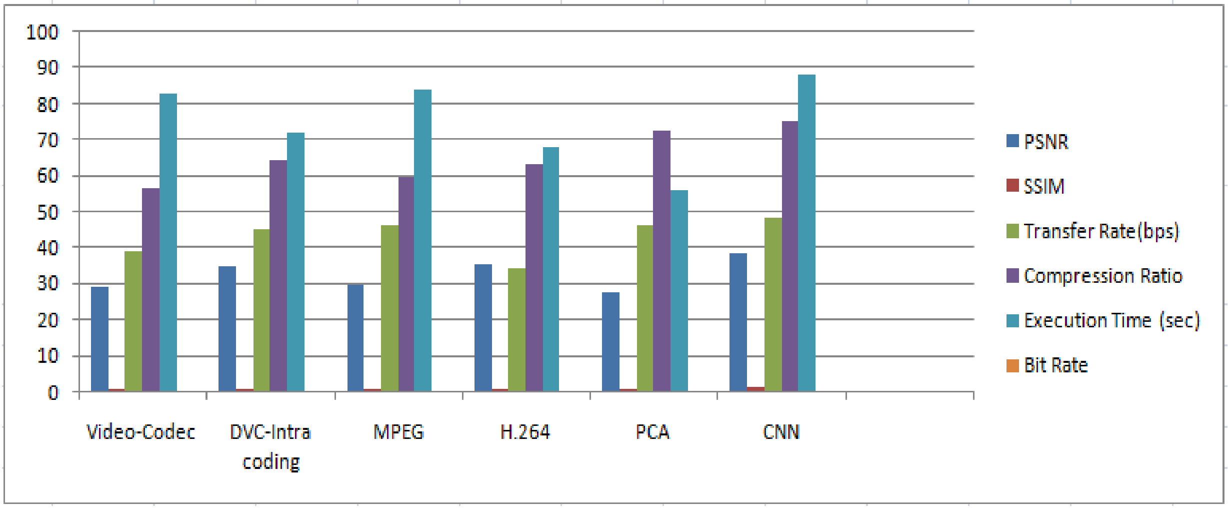

Fig. 4.3: Comparision Results for video -2

From the above Table3. lack of trade levels in quality, compressed data and transferring date, which depend on the selection of pixels and operation between frames. These problems are overcome by with proposed algorithm. The proposed output has good quality of picture of compressed video and good similarity results compared with input data.

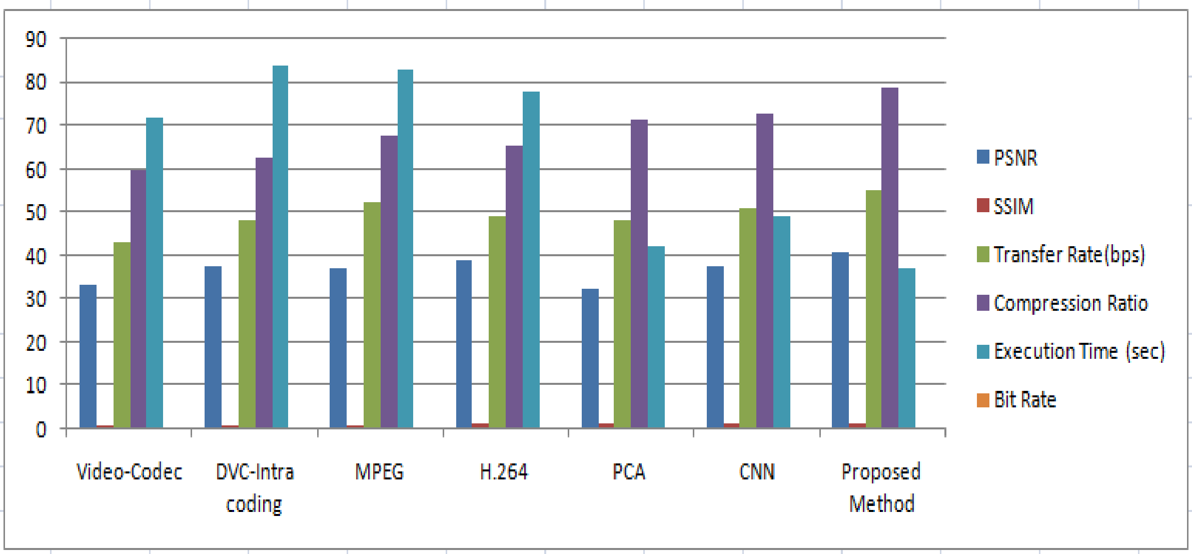

Fig. 4.4: Comparision Results for video -3

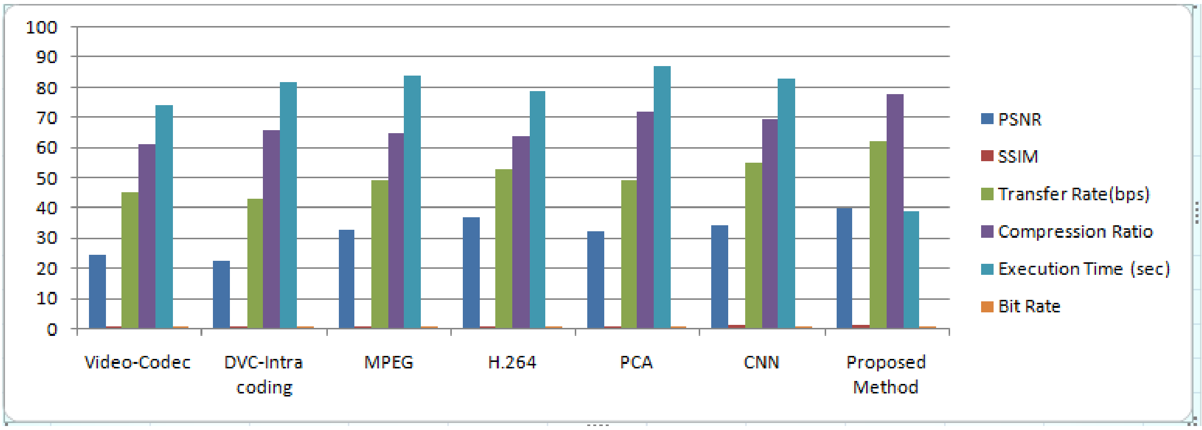

Fig. 4.5: Comparision Results for video -1

It can be said that the proposed algorithm is rather efficient to achieve the maximum compression but keep the high video quality. Each of the other methods has continuously had higher bit rates (0.41-0.55 bps), thus showing greater compression efficiency. It can be seen specifically in the PSNR and SSIM results, where the proposed technique saves not only the bit rate, but also ensures the quality is quite high. These findings show that the proposed method has the high potential of yielding a massive minimisation of data size, with negligible or visual loss that is of great importance in the case of video streaming and storage services where bandwidth and storage limits cannot be avoided. The old technology, including MPEG and H.264, offers powerful compression ratios yet elevated bit rates (range between 0.52 and 0.75 bps) and lesser PSNR and SSIM than the current technique.

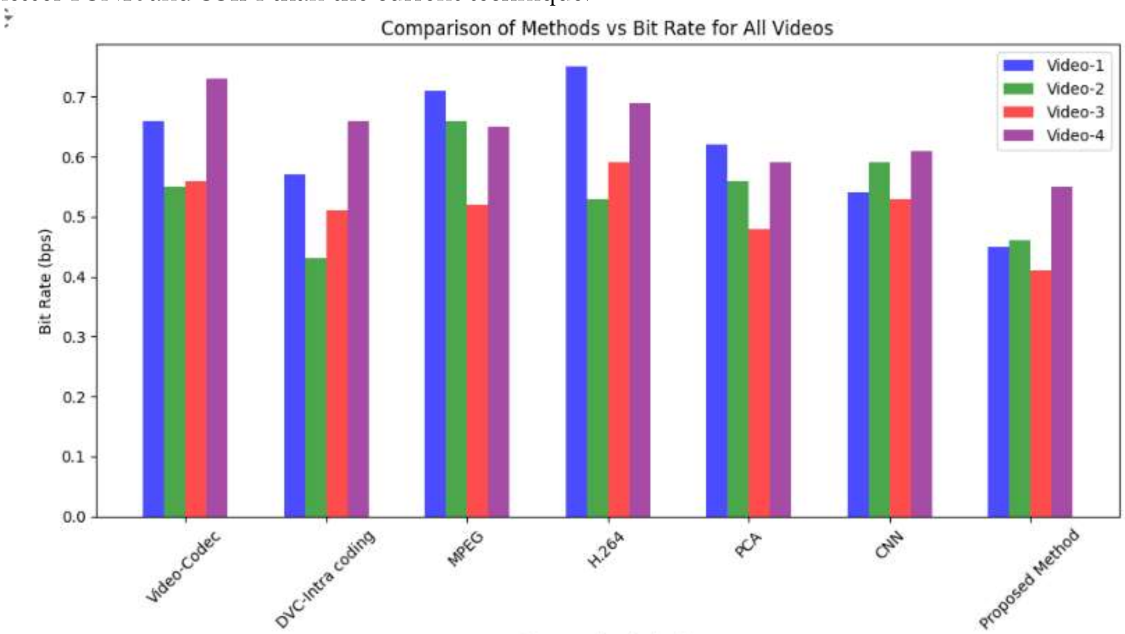

Fig. 4.6: Comparision Results for video -1 (Bit Rate)

Although these techniques are less effective in reducing data, they are nonetheless helpful for applications where a higher bit rate is acceptable. Despite having lower bit rates than MPEG and H.264, CNN and DVC-Intra Coding produce outcomes that are moderate, but they are still not as effective as the Proposed Method overall, especially when considering both compression and quality retention. Despite having a lower compression efficiency, the PCA approach shows that more complex deep learning-based algorithms may perform better than simpler ones.

The Proposed Method is a better technique of compressing videos compared to the rest of the methods because it surpasses them in many performance measures. It returns the PSNR (37.34 dB) and SSIM (0.828) highest among other evaluated algorithms including CNN (23.32 dB, 0.793), PCA (32.65 dB, 0.549), etc., showing a better ability of the pictures to retain video quality. Moreover, Compression Ratio (78.66) is more than the standard techniques like MPEG (52.45) and H.264 (54.34) and hence it is efficient to reduce the file size and at the same time retain quality with the variation of Video-1 data. Various videoes are used to test these results and they perform better.

V. CONCLUSION AND FUTURE SCOPE:

In the present paper algorithms of intra and inter-coding methods have been conducted by the principal component analysis and Quad Tree with Nested Multi-type techniques. The technique is set to comparison with other common lossy/lossless compression standards. Such an approach produces advanced results in video compression, and transmit encoding method in 5G networks. Quad Tree and Nested Multi-type Tree of the Machine learning algorithm constitutes 5G Applications is appropriate for high performance dimensionality reduction and compression which in the aspect of video compression never depicted good performance. The intra coding techniques are capable of being effected by Quad Tree in nested multi type. The technique is such that they are not only video compressing but also applicable on different forms of video formats as 5 G networks on digital television applications of low bit rate storing or transmission of data. These values are provided with sophisticated values of the compression Ratio and PSNR as opposed to the other existing techniques.

REFERENCES

1. TVK Moorthy, AK Budati, S Kautish, SB Goyal, KL Prasad, “Reduction of satellite images size in 5G networks using machine learning algorithms”, IET Communications, 2022. Vol. 16(5), pp.584-591.
2. Asmae Mamane,Mohammed Fattah,Mohammed El Ghazi,Moulhime El Bekkali, 5G Enhanced Mobile Broadband (eMBB): Evaluation of Scheduling Algorithms Performances for Time-Division Duplex Mode, “International Journal of Interactive Mobile Technologies”,2022. Vol.16(1), pp. 120-131.
3. European Commission: 5G: Challenges, Research Priorities, and Recommendations – Joint White Paper. European Commission, “Strategic Research and Innovation Agenda” (2014)
4. Q. Shi and H. Sun, Image And Video Compression for Multimedia Engineering: Fundamentals, Algorithms and Standards, “Image Processing Series”. Taylor & Francis Group, 2008.
5. B. G. Haskell, P. G. Howard, Y. A. LeCun, A. Puri, J. Ostermann, M. R. Civanlar, L. Rabiner, L. Bottou, and P. Haffner, Image and video coding-emerging standards and beyond, “Circuits and Systems for Video Technology”, IEEE Transactions on, 1998.
6. G. K. Wallace, The JPEG still picture compression standard, “Consumer Electronics”, IEEE Transactions, 1992. vol. 38(1), pp. xviii–xxxiv.
7. M. Rabbani and R. Joshi, An overview of the JPEG 2000 still image compression standard, “Signal processing: Image communication”, 2002. Vol.17(1), pp.3-48.
8. Furht, J. Greenberg, and R. Westwater, Motion Estimation Algorithms for Video Compression, “ Kluwer Academic Publishers”, Norwel, MA, 1997.
9. Chen, Z., He, T., Jin, X., Wu, F.: Learning for video compression, “ IEEE Transactions on Circuits and Systems for Video Technology” 2019.
10. G.-L. Chen, J.-S. Pan, and J.-L. Wang, Video encoder architecture for MPEG2 real time encoding, “IEEE Transactions on Consumer Electronics”, 1996. vol. 42, pp. 290-299.
11. T Venkatakrishnamoorthy, GU Reddy, Cloud enhancement of NOAA multispectral images by using independent component analysis and principal component analysis for sustainable systems, “Computers & Electrical Engineering” 2019. Vol. 74, 35-46.
12. M Dharani, G Sreenivasulu, Land use and land cover change detection by using principal component analysis and morphological operations in remote sensing applications, “International Journal of Computers and Applications”, 2021, Vol. 43(5), pp: 462-471.
13. D.Marphe, H.Schwarz, Video Compression Using Nested Quadtree Structures, Leaf Merging, and Improved Techniques for Motion Representation and Entropy Coding, Computer Science, “IEEE Transactions on Circuits and Systems for Video Technology”, 2010.

14. E. Chan, A.A. Rodriguez, R. Gandhi, and S. Panchanathan, Experiments on BlockMatching Techniques for Video Coding, "Journal of Multimedia Systems", 1994. Vol. 2(5), pp. 228-241.
15. Venkatakrishnamoorthy, T., Srinivas, B., Dharani, M., ...Reddy, Y.D.R., Supriya, P., Design of Multi-Layer Protocol Architecture using Hybrid Optimal Link State Routing (HOLSR) Protocol for CR Networks, "International Journal on Recent and Innovation Trends in Computing and Communication", 2023. Vol.11, pp. 419–423.
16. Junwei Zhou, Yincheng Fu, Yanchao Yang, Anthony T.S. Ho, Distributed video coding using interval overlapped arithmetic coding, "Signal Processing: Image Communication, 2019. Vol.76, pp.118-124.
17. J.R. Jain, and A.K. Jain, Displacement Measurement and Its Application in Interframe Image Coding, "IEEE Transactions on Communications", 1981. Vol. 29, pp. 1799-1808.
18. R. Westwater and B. Furht, Three-Dimensional DCT Video Compression Technique Based on Adaptive Quantizers, " Second IEEE International Conference on Engineering of Complex Computer Systems", Montreal, Canada, October 1996.
19. G. J. Sullivan and J.-R. Ohm, Recent developments in standardization of high efficiency video coding (HEVC), "in Proc. SPIE" , 2010, vol. 7798, pp. 77980V
20. Daoud, A., Jordán, F., Sharma, M. et al. . Satellite Images and Deep Learning to Measure Health and Living Standards in India. "Soc Indic Res", 2023. Vol. 167, pp.475–505.
21. Zhewen Sun,Li Yu,Wei Peng, QTMT-LNN: A fast intra CU partition using lightweight neural network for 360-degree video coding on VVC, "IET Image Processing" 2002. Vol. 17(5), pp. 597-612.
22. M. Dharani, M. Bharathi, N. Padmaja and K. Praveena, Design and Verification process of Combinational Adder using UVM Methodology, "International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS)",2023. Bangalore, India, 2023, pp. 359-362, doi: 10.1109/ICAECIS58353.2023.10170273.
23. Bharathi, M., Prasad, D., Venkatakrishnamoorthy, T., & Dharani, M. Diabetes diagnostic method based on tongue image classification using machine learning algorithms, "Journal of Pharmaceutical Negative Results", 2022. 13(4), 1247-1250.
24. Xiwu Shang , Guoping Li a, Xiaoli Zhao , Yifan Zuo, Low complexity inter coding scheme for Versatile Video Coding (VVC), "Journal of Visual Communication and Image Representation", Vol. 90, February 2023, 103683.