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Generative Adversarial and Dual Layered Deep Classification Techniques for Improving Block Constructions in Public Cloud

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Abstract: *This paper provides the Generative Adversarial and Dual Layered Deep Classification techniques to improve the drawbacks in the methods of Absolute Moment BTC (AMBTC) technique in reconstruction error rate of standard BTC model. The image blocks generation and compression are the main phases of BTC model. This can be applied for both colour images and grey scale images. However, the conventional BTC procedures lacks for edge reconstructions and noise reductions in the output images. The first technique GABTC is developed with multi-layered Deep Neural Network (DNN) structures with GA neural models. The integration of both GA models and BTC principles improve the quality of block constructions and reconstructions significantly. The second proposed work is adopted the Dual layered Deep Classification Technique. Handling the image database with minimal storage complexity, minimal computational complexity and optimal quality is a significant task. To obtain these solutions, many image processing techniques are evolved. In the domain, image compression and decompression are more needed at any cost for effectively handling the complex image databases. E-Learning resources are widely used around the internet based knowledge sharing environments. In the E-Learning environment, multiple types of data resources are managed. Particularly, organizing the images is more crucial task where multiple qualities of images are appeared inside the E-Learning network databases. This problem expects solutions from effective image compression techniques. Block Truncation Coding (BTC) and Absolute Moment BTC (AMBTC) are the techniques provide useful and easy implementations of E-Learning based image compression platform. At the same time, they are limited to image dissimilarity rate. To maintain the quality of images in both compression and decompression phases, multilevel image analysis models and training phases are required. In this regard, this proposed system develops a Dual Layered Deep Classification and Truncation (DLDCT) technique. DLDCT comprises the baseline benefits of BTC, multi-layered Support Vector Machine (SVM) units and Deep Layered Convolutional Neural Network (DLCNN) for producing classified range of image pixels and compressing the images under controlled circumstances. This proposed DLDCT makes the image compression and decompression with determined observations. This reduces real time errors occur during image reconstruction phases. This proposed system has been implemented and compared with existing works with respect to significant performance parameters.*

Keywords: Drug

I. INTRODUCTION

The BTC method is not providing good quality of image through the content based retrieval and image based retrieval image processing techniques. The BTC primarily based totally compressions decomposes a picture right into a bitmap picture and color quantizes that are in the end exploited for deriving the picture characteristic descriptor. The characteristic derived from bitmap picture characterizes the data of the spatial styles of the blocks. The different characteristic derived from color quantizes characterizes the data of the color correlation in the blocks. Generative compression, maintaining the overall photo content material at the same time as producing shape of different scales which include leaves of timber or home windows with inside the facade of buildings, and selective generative compression, absolutely producing elements of the photo from a semantic label map at the same time as maintaining user-described areas with an excessive diploma of detail.This proposed GA-BTC is implemented with the help of BTC

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based block formation, block oriented GAN computations (Generative and Discriminative Functions), disjoint image distribution solutions, DNN based encoding and decoding, DNN based compression and decompression. In addition, this proposed model uses pixel masking for reducing the blurred image portions. These collective procedures improve the quality of entire image compression and decompression system. This improves the functionality of entire e-learning image management system. According to the modified BTC algorithm the image divided into blocks and stored as compressed image based on the flexible storing environment.

1.1. BTC Compression Based Features

Online learning resources and the databases are heavily depending on versatile multimedia data (text files, audio files, video files and image files). As data used in internet platform increases, the database technology goes for utilizing data compression and decompression techniques for handling the data transmissions in light weight manner. In the input stream of multimedia data, many data points are categorized under various characteristics such as size, quality and format etc. In E-Learning database management systems, maintaining flawless data resources and qualities in them are more necessary tasks. This work finds the image resources of E-Learning environment.

Images are considered and classified based on pixel characteristics. The pixel values and the image modes (grey scale and color images) playing important roles in image handling databases. Images take various range of storage spaces depend on the quality. The pixel quality of any image is easily compromised where conventional image compression techniques are preferred over effective techniques. As image compression and decompression techniques are important to maintain the effective storage assurance policies in E-Learning systems. At the same time, compromising the quality of images are not acceptable at the reconstruction process.

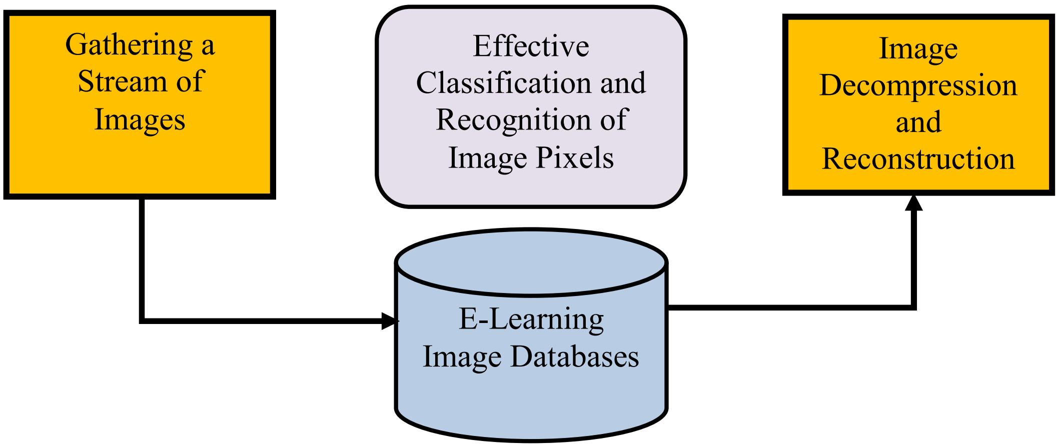

Figure 1: E-Learning Images and Compression Functions

Images are reconstructed using many techniques once they are decompressed. In this process, BTC and AMBTC techniques are enriching the image compression quality based on block truncation models. In these coding techniques, each image block is determined with numerical pixel contents and they are truncated to produce reduced set of images. In another end, BTC and AMBTC are reconstructing the images to the original status.

However, they are lossy image compression techniques. As they are conventional lossy techniques, the observations are not optimal for attaining the best image qualities throughout the compression and decompression functions. Thus the need for analyzing image pixels is more important before starting image coding or any compression tasks. For image analysis, many data analysis models, Machine Learning (ML) techniques and Deep Learning (DL) techniques are widely applied over the data world.

Many recent researches are initiating intelligent image compression techniques. However, they are consistently focusing on common image types and homogeneous image databases. This research problem can be resolved by using proposed DLDCT technique. In this proposed technique, image pixels are effectively classified and weighted under various characteristics to apply the compression strategy in an optimal way (Multi-Classifier SVM). At the same phase, the DLCNN techniques are taken for pixel content analysis model. These techniques are supporting the image compression and decompression units to work effectively. On the basis of BTC platform, the proposed techniques are developed to achieve more accurate pixel manipulation and image compression processes.

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1.2. Generative Adversarial Networks

Generative Adversarial Networks, are a method to generative modelling the usage of deep getting to know methods, including convolutional neural networks. Generative modelling is an unmanaged getting to know in gadget getting to know that includes routinely coming across and getting to know the regularities or styles in enter facts in any such manner that the version may be used to generate or output new examples that plausibly might have been drawn from the authentic dataset.

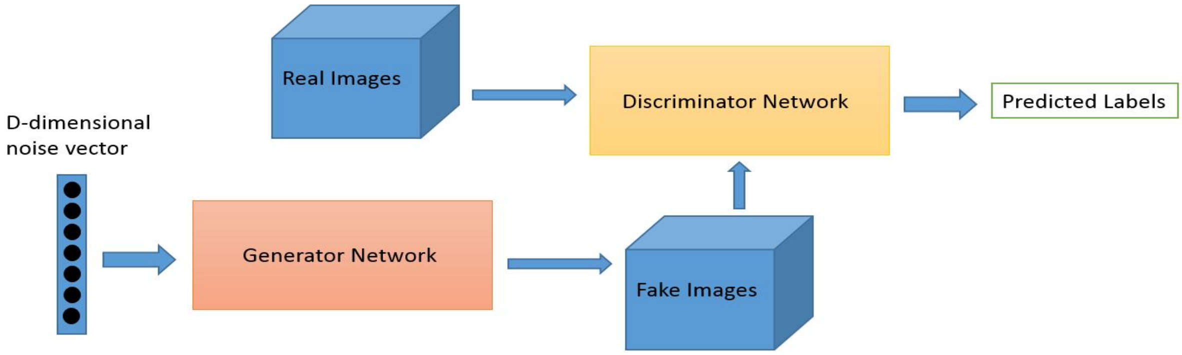

Figure 2: GAN Architecture for Image Modelling

GAN consists of two models like generative model, descriptive model. In generative model the image initially checked whether it is an original image or artificially created image, based on the conformation it will split the images into discriminator part named as labels. The generator model designed on the various iterations of images whether it may be natural or artificial. An efficient generator models management of the database in e-learning resource environment is always a challenging task for any database administrator. E-learning databases are containing text files, image files and other multimedia files in distributed manner. These files are usually created at different platforms and delivered to various nodes. In this regard, they are completely heterogeneous in nature. Comparing to other e-learning resources, image databases are more vulnerable and dependent on the node based applications. Thus the image compression and reconstruction procedures are need to be taken significantly to maintain the image quality in both ends.

Image compression techniques and decompression techniques are widely depending on the phases of image coding principles. The effective coding and decoding makes the image with less errors in pixel values. In this situation, many image compression techniques were proposed and implemented to keep the image quality at the reconstruction end takes random input values and convert them into image pixels through evolutional network.The efficient management of the database in e-learning resource environment is always a challenging task for any database administrator. E-learning databases are containing text files, image files and other multimedia files in distributed manner. These files are usually created at different platforms and delivered to various nodes. In this regard, they are completely heterogeneous in nature. Comparing to other e-learning resources, image databases are more vulnerable and dependent on the node based applications. Thus the image compression and reconstruction procedures are need to be taken significantly to maintain the image quality in both ends.

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GAN is a kind of DNN that has two internal phases such as generator phase and discriminator phase. For a given image pixel set, S^{Pixel}, GAN layer are constructed to observe hidden distribution of pixels using the generator function, G^{NF}. This function is trained to observe the range of pixels' properties and intensities. This function is executed by different GAN layer neurons in parallel manner. For a given heterogeneous image set $'I'$, this generator GAN function observes the detailed pixel distributions and the ranges. At the same time, the discriminator function, D^{NF} helps to extract the pixel variations and reconstruction qualities for various images. This quality of GAN is providing the best impact in quality image reconstruction process. This is achieved through complex DNN layers and neural weight evaluation procedures. The detailed construction procedures of BTC, GAN and GA-BTC are given in next section. Discriminator network takes as input and returns the image compression and quality of image should be improved compared to modified BTC. It have to design the discriminator and generator based on the various parameters.

II. GABTC DEVELOPMENT STRATEGY AND ALGORITHM

Standard BTC algorithm divides the given image (color or grayscale) in to n X n sub blocks and reduces the pixel quantities within the divided block. This BTC uses image quantize function, $Q(I)$ for all images of e-learning environment. This image handling function minimizes range of pixel characteristics according to local database circumstance. In addition, these blocks are encoded using dual-line quantize that creates two quantization points $Q1\ and\ Q2$ for all image blocks. This standard model formulates two more parameters such as mean and deviation $m\ and\ d$ for all blocks. According to these parameters, each image pixels are encoded and decoded by comparing with $m\ and\ d$ values of each block.

2.1. BTC Design

Once the input image, $'I(i)'$of the image dataset $'I'$is segmented in to n blocks, each block, $'I(i,b)'$ is encoded with the help of dual signal functions. The range of each $'I(i,b)'$ block is measures in terms of primary pixel samples. Assume $'I(i)' = n * n$ and the values of image pixels in a block, $'p(i,b)'$ can be denoted as $'v(i,b)', i = 1,2,3 \ldots .k$. As this standard BTC uses one bit quantizer function, the outputs are determined using two quantizer values, $Q1\ and\ Q2$. Equation denotes the formulation of $Q1\ and\ Q2$.

$$v(i,b)^I \geq v(i(t),b)^I \quad : Q1$$

$$v(i,b)^I < v(i(t),b)^I \quad : Q2$$

Here, $i(t)$ is determined as pixel range threshold. Now assume, $q(i,b)$ is the total number of $v(i,b)^I$ s larger than $v(i(t),b)^I$ then, $Q1\ and\ Q2$ are determined by the deviations, $m\ and\ d$. In this proposed system, totally 2450 images are managed in e-learning library system. These images are different in terms of size, type, and qualities. In other words, they are completely heterogeneous in nature. However, this BTC produces the basic image compression and pixel quantization procedures, this conventional mechanism raises crucial range of Mean Square Error (MSE). Thus BTC is not sufficient to handle bulk e-learning images that to be compressed. The sample image compression and reconstruction procedures are given in pixel values as shown below.

3	13	13	13
3	13	13	3
3	13	13	13
3	3	3	13

Q1=3::Q2=13

3	10	11	9
3	9	11	4
3	13	12	10
5	2	4	12

m=9 :: d=4.89

0	1	1	1
0	1	1	0
0	1	1	1
0	0	0	1

$q(i,b) = 9$

Table 1 : BTC for Image Compression and Decompression

The determinations of standard BTC are not closer to minimal error circumstances as illustrated above. As given, the reconstructed values are determined with two static extends. This reduces the quality of reconstructed images. In this condition, the BTC is improved with various features to produce less MSE than conventional techniques.

2.2 Modified BTC Variants and Limitations

To improve the quality observations of standard BTC technique, AMBTC has been invented as a BTC variant. In this technique, the values such as $m\ and\ d$ are retreated as upper mean and lower mean $U'm\ and\ L'm$ respectively. According to these determinations, every image block pixel values are treated with different groups based on the ranges of $U'm\ and\ L'm$.

3	10	11	9
3	9	11	4
3	13	12	10
5	2	4	12
$U'm = 9, L'm = 4$			

0	1	1	1
0	1	1	1
0	1	1	1
1	0	1	1
$q(i, b) = 12$			

3	13	13	13
3	13	13	4
3	13	13	13
13	4	13	13
Q1=4::Q2=13			

Table 2: Modified BTC

In this comparison, for the same image values, the later one produces less deviations in reconstructed image. On the scope, many BTC variants have been proposed to minimize the MSE, MAE and loss rates. In addition, there is a need for improving Peak Signal to Noise Ratio (PSNR) for all e-learning based heterogeneous images. This need cannot be achieved without using complex image training models and neural functions.

ML and DL techniques are proposed to build intelligent image compression techniques that produce optimal loss in reconstruction phase. Among the techniques, DNN and RNN structures are widely taken for research fields. In the proposed system, the BTC functions and observations are trained with the help of novel GA-BTC principles. GAN architectures are naturally complex and produce variants in the neural layers. Several image processing and compression techniques are proposed using GAN principles. However, BTC based GAN and DNN development are novel to research fields. The integration of both BTC and GAN neural structures delivers simplicity in image value manipulations and complexity in pixel evaluations. Thus the proposed system has been designed to produce efficient GA-BTC techniques for implementing e-learning image resources. GAN framework for full resolution photo compression and use it to construct an excessive photo compression system and also provide the primary to very well discover the sort of framework with inside the context of full-decision photo compression. The new image compression in visible pleasant primarily based totally on a consumer study, with dramatic bitrate savings. Deep neural networks provide the image compression model for lossless compression method of high quality image with help of auto decoders and encoders methods. This network converts the image into bit stream and the bit's tram may be convert into segments of zeros and ones in the networking neurons.

2.3 Algorithm

Let assume, an image (color or gray scale), $'I(i)'$ is given as an input for the segmentation function of BTC (BTC segmentation function), $'B(s)'$. This function creates $'n\,X\,n'$ individual image blocks, $'I(i,b)'$. As discussed earlier, pixel components of each block have been measured. The generator function, G^{NF} is trained with image samples and pixel values in order to match the discriminator function, D^{NF} for observing minimal and maximum pixel ranges for each image block, $'I(i,b)'$.

$$L_{GAN}(I) = \sum_{i=0}^{N} Max(DE).EN[D^{NF}('I(i,b)' + EN[G^{NF}(I(i,b)')] - -$$

$$L_{GAN}(v,I) = \sum_{i=0}^{N} Max(DE).EN[D^{NF}('v(i,b)' + EN[G^{NF}(v(i,b)')]$$

Equations illustrates the internal representations of segmented image blocks and their encoding procedures with respect to the DNN layers ($G^{NF}$and D^{NF}). In these equations, $L_{GAN}(I)$ and $L_{GAN}(I,v)$ denote the min-max pixel components of cumulative image blocks created by BTC segmentation principles. In this case, DE and EN denotes the decoding and encoding functions applied on each image functions. In this proposed DNN, both G^{NF} and D^{NF} are complete scalar image functions. In this case, $Min(L_{GAN}(v,I))$ delivers the minimal rate of pixel divergence at the end of image decoding phase. DNNs of GAN unit have more number of complex image component analysis layers with respect to the input variances.

GAN is a kind of adversarial manipulation DNN that finds the absolute divergence rate of each encoding and decoding processes. This means that the divergence rate is determined with the help of D^{NF}. In extend, this work uses controlled GAN structures that uses joint and disjoint pixel distributions of each image blocks.

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Generally, the standard BTC and other BTC variances are manipulating the image block details with the help of randomly computed threshold values. This kind of manipulation is not sufficient for reducing the MSE. This existing mechanism may not bother about the uncertain or other hidden distributions of any image blocks. Thus the image decompression produces more error. In this work, this problem has been resolved using following determinations. In the proposed system, the disjoint or uncertain pixel components are represented as

$$U('v(i,b)') = \sum_{i=0}^{N} f(Xi,bi).\tau$$

In the equation, (Xi,bi) gives the disjoint values of respective block with respect to deviation factor, τ.For doing DNN based image compression and look alike decompression, the following steps are taken as shown in algorithm

Algorithm GA-BTC

Input: $I(i,b), samples, EN, DE$

Output: *Results from* G^{NF} and D^{NF}

Begin

Step 1: *Set the DNN encoder and decoder functions as* EN, DE *respectively*

Step 2: *Define the loosely operative quantizer,* $Q.l$. *Let the levels are*

$$Q.l = \{q1, q2, \ldots qn\} ------(4.6)$$

Step 3:*Do the DNN encoding procedure with respect to observed pixel representations,*

$$R(I(i,b)) = Q(EN(I(i,b)) ----- (4.7)$$

Step 4:*Convert the block components in to bits*

Step 5: *Execute* $L_{GAN}(v,I)$ *and* $U('v(i,b)')$ *functions for all blocks*

Step 6: *Do effective sample collection and reconstruction with respect to*G^{NF} *and*D^{NF}

Step 7: *Determine MSE and MAE*

Step 8: *Repeat* G^{NF} *and* D^{NF}

End

Algorithm describes proposed GA-BTC procedures for handling the image components with joint and disjoint distributions.

In this DNN based image compression, the various image processing functions are implemented using appropriate training and differentiation methodologies as shown in figure In this novel strategy, the following functions are implemented for improving the quality of reconstructed image (decompressed) .

- Simple BTC based image block manipulation
- Uncertain GAN generative training function
- GAN associated image block encoding procedures
- GAN implemented quantizer function
- Quantized observation function
- GAN associated image block decoding procedures
- Uncertain GAN discriminator training function
- Image reconstruction function

In this approach, BTC based image segmentation and block formation are conventional approaches as given in equations. The GAN generative function uses optimal image samples for increasing the training efforts to update e-learning knowledge base. This static and uncertain GAN generative image compression procedures are given in equations

$$= \sum_{i=0}^{N} EN[D^{NF}('v(i,b)'] + EN[G^{NF}(v(i,b)')] + eEN(v(i,b)')$$

$$Range(L_{GAN}(v,I))$$

$$= \sum_{i=0}^{N} EN[D^{NF}('v(i,b)'] + EN[G^{NF}(v(i,b)')] + eENv(i,b)' + U('v(i,b)')$$

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In the equation, eEN denotes encoding distortions. In equation, the GAN function is implemented for attaining uncertain or disjoint pixel attribute collection for producing better image reconstruction. In both cases of GA-BTC implementation, generative functions and discriminator functions are formulated with DNN encoding layers and decoding layers. At the same time, these functions infer in image compression and decompression phases. Once the values of all image blocks are effectively encoded with minimal distortions, the compression and decompression quality automatically increases. In addition, the propose GA-BTC use partial image block compression and masking techniques to hide the particular block's pixel value to ignore the explicit distortions identified at the end. The partial block masking phase of GA-BTC is defined as given in equation. These complex training procedures and DNN based block compression (truncation) techniques reduces the limitations of BTC and other BTC variants in many aspects.

$$DE\big(I(i,b)\big) = \sum_{i=0}^{N} f^{i}\Big(M.b\Big(EN\big(I(i,b)\big)\Big)$$

The equation shows the bit masking function, $M.b$ for all encoded images. This function is integrated with decoding phase of image blocks. At the same time, this function is taken by image reconstruction procedure for all image blocks in need. This is illustrated in equation.

$$n^{1} * I(i,b)' = \sum_{i=0}^{N}\sum_{j=0}^{M} f^{i}\Big(M.D^{NF}\big[DE\big(I(i,b)\big)\big]\Big) \pm er$$

In equation, er is reconstruction bias. These proposed techniques are using BTC for image block constructions that initiates limited computation overhead. In addition, the GAN based DNN functions are enriching the quality of training phases, compression and decompression phases gradually. The proposed GA-BTC is implemented and performance is compared with more relevant works. Section 4 shows the system implementation details. The mentioned GAN have lot of combined conditional GAN's and learned supervisor method for optimizing the image in the E learning environment. For simplicity formed a single channel binary heat map image n with pixel size of 16 x 4 x 4 to storing the image in the synthesized manner. The DNN have synthesized regions to have the original metrics values of the images and extract the original quality without compromising the content.

III. PROPOSED SYSTEM FOR DUAL LAYERED DEEP SYSTEM

The proposed system initiates BTC for making image block (color and greyscale) at the first phase. Under this BTC model, the set of images are treated as a collection of relative blocks, B^{img}. Each image block, $B^{img}(I)$ has been determined with observed and uncertain pixel components. They can be denoted as, , $P\_O^{img}(B.I)$ and $P\_U^{img}(B.I)$ respectively. BTC, the base model constructs the units of each block as the decimal representation of pixel values. In this condition, each block, $B^{img}(I.i)$is manipulated to produce block-level mean, and variation factors, such as $m(B^{img}(I.i))$ and $v(B^{img}(I.i))$.

In the next phase, Nonlinear Ensemble Multi-level SVM (NEMSVM) classifiers are implemented to identify the pixel ranges and the group of block components. The collection of NEMSVM sub classifiers are trained to group the given input of heterogeneous image contents (pixel values). The classifiers are attached for multiple image blocks such as denoted in equation (1).

$$C(L) = \sum_{i=1}^{N} C[P\_O^{img}(B.I) + P\_U^{img}(B.I)] \ \forall \ (B.I)$$

These classifiers associated with multiple image blocks act independently to produce collective classified results. The outcomes of NEMSVM units are produced for the next level convolutional filtering processes. These filtering processes are executed on the basis of classified pixel components with the help of DLCNN layers.

DLCNN is a deep CNN works effectively on various image blocks and block pixels produced by NEMSVM units using multi-level ConvNet filters. This ConvNet for handling classified pixel elements are given in equation.

$$CON(N) = \sum_{i=1}^{C} C(L).F^S.P^S.S^S.d \quad \forall \ (B.I)$$

Equation shows, $P^S \text{ and } S^S$ are the padding and stride determinations. In addition, F^S and d illustrate filter size and bias rate of designed ConvNets of DLCNN. This multi-level DLCNN takes and analyses the variances and deeply extracted pixel components. Thus the proposed system deeply implements image compression and reconstruction phases with optimal losses compared to any of the recent works.

3.1 Technical Details and Algorithms

The input greyscale image or color image of an E-Learning image database can be considered as, $I(i(t))$. The input images of database are converted in to grid-level blocks in the dimension, $n * m$. The converted image matrix is represented as $I(n * m)$.

In the matrix, $I(n * m)$, each image cells or blocks are coordinated with respective row and column. An image block, $B^{img}(I)$ *located at* $B^{img}(n * m)$ *in* $I(n * m)$ is identified with the values of pixel contents. Each $B^{img}(n * m)$ *in* $I(n * m)$maintains completely various pixel properties in terms of density, intensity, noise rate, frequency rate and etc.

In the image, the pixels of each block are categorized in to deterministic and nondeterministic classes with the help of Hidden Markov Model (HMM) functions. The baseline BTC is enabled with HMM to produce first level optimal encoded outputs. In this case, the block level coding has been executed as shown in equations

$$P\_O^{img}(B.I,i) \geq P_o(T,B.I)^I : B(Q1)$$

$$P\_O^{img}(B.I,i) < P_o(T,B.I)^I : B(Q2)$$

$$P\_U^{img}(B.I,i) \geq P_o(T,B.I)^I : B(Q1)$$

$$P\_U^{img}(B.I,i) < P_o(T,B.I)^I : B(Q2)$$

These equations are used to manipulate the BTC quantized values for both deterministic and nondeterministic pixel contents.

$$I(n * m) = \sum HMM(B(i,p))$$

The computations of both deterministic and nondeterministic values of pixels are illustrated in Table. However, these computations produce notable MSE and MAE with limited PSNR for image compression and decompression phases. In the values given in Table, BTC associated HMM is applied for detecting uncertain conditions of image qualities but with real time limitations.

4	9	10	11	4	13	13	13	0	1	1	1
7	5	5	6	13	4	4	4	1	0	0	0
7	9	10	11	13	13	13	13	1	1	1	1
5	13	13	13	4	13	13	13	0	1	1	1
$m(B^{img}(I.i))$=7 $v(B^{img}(I.i) = 3.76$				*B(Q1) =4* *B(Q2)=13*				$BQ(i,B.I)$ =11			

Table 5: BTC and HMM Determinations

These values are not more specific in terms of minimal MSE and MAE. However, the baseline BTC and HMM determinations are initiated into NEMSVM classifier units with suitable training samples.

3.2 Multi-Level Classification Using NEMSVM

Let the image training samples for any image database is identified as $T(S.I)$, illustrated in equation.

$$T(S.I) = \sum Samples\ (B.I,p).\frac{ds}{dt}$$

The samples, $T(S.I)$ are collected with respect to various time intervals for different pixel blocks. In addition, sample dataset or training dataset has been created for evaluating the pixel elements. Based on these pixel sample set, NEMSVM initiates $T(N)$ classifier units (sub classifier units) with dissimilar SVM threshold parameters, $T(C)$ for NEMSVM classifier , $C(L)$ as given in equation.

The classifier units are formulated with threshold variances, mean variances and per block deviations.

Algorithm 1: NEMSVM

Input: $P\_O^{img}(B.I,i)$ *and* $P\_U^{mg}(B.I,i)$

Output: $C(L.i)$ *and* $C(L)$

Begin

Step 1: *Set SVM classifier units*

Step 2: *Formulate Thresholds,* $T(C.i)$ *for* $C(L.i)$ *units*

$$T(C.i) = f(m(B^{img}(I.i)) \pm v(B^{img}(I.i)).\emptyset$$

$\emptyset - Threshold\ Biase$

Step 3:*Implement a sub classifier of NEMSVM,*$C(L.i)$

$$C(L.i) = f\big(B(i,po),T(C.i)\big).dt$$

Step 4:*Construct a NEMSVM block for all image blocks as given in equation (1)*

Step 5: *Collect and analyze nondeterministic pixel values under isolated classes.*

$$C(L.i) = f\big(B(i,pu),T(C.i)\big).dt$$

Step 6: *Do optimal sample collection iteratively and redo NEMSVM constructions*

Step 7: *Determine the bias rates.*

Step 8: *Repeat*

This NEMSVM produces both linear and nonlinear observations of image block pixels at different time intervals with deeply collected samples. The baseline nonlinear SVM is illustrated in figure

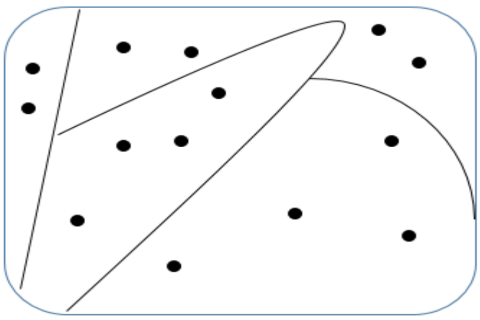


Figure 3: NEMSVM Threshold Curves

Figure shows multiple support vectors lines including linear and nonlinear object classifications. In this proposed system, the image samples are taken into both linear and nonlinear pixel evaluations. At the same time, the pixel components are classified under deterministic and nondeterministic nature of images. In this manner, the proposed DLDCT produces multi-level block classification units. These units are iteratively trained by various new image samples in need to improve the classification accuracy rate. These classified results are enclosed with DLCNN layers as deep training sets.

This NEMSVM observations and the training sets are enriching the CNN based computations that are running based on DNN foundations.

3.3. DLCNN on Deep Image Learning, Compression and Reconstruction

CNN is a DL technique used to analyze images using effective ConvNet filtering techniques. In this proposed system, the BTC enabled image blocks and NEMSVM observations are given into DLCNN units. Let the image is given as 4*4 matrix, C^Mthen the ConvNet filters of DLCNN are determined at the range of 2*2 matrix, F^M. Consequently, the DLCNN initiates the deeply constructed results gathered from NEMSVM and BTC blocks. These classified datasets are used for DLCNN operations.

In this DLCNN technique, each block pixels of deterministic and nondeterministic conditions are evaluated under multi-level evaluations. The filters of DLCNN are implemented for series of DNN layers that contains image evaluation functions. In this deep CNN based analysis process, the given E-Learning images are strongly weighted using various image parameters such as pixel intensity, pixel quantity in a block, pixel distortions, average block noise ratio, overall image noise ratio, frequency variations and uncertain image components. Figures shows the DLCNN computations and the ConvNet filters.

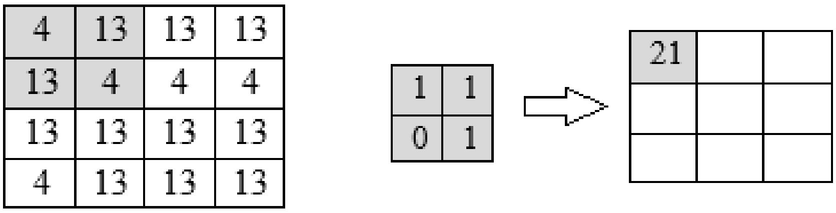


Figure 4: DLCNN Iteration 1

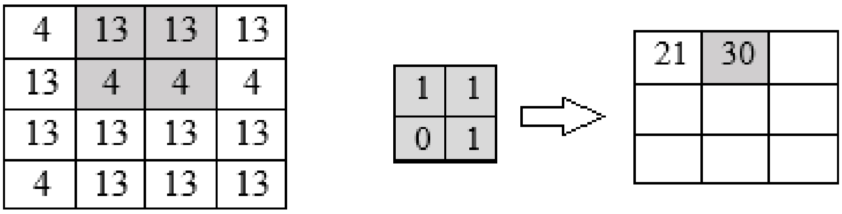


Figure 5: DLCNN Iteration 2

The computations are executed by DLCNN to find the deep observations as illustrated in equation.

$$C^M.F^{M}_{I} => B_I$$

For each iteration, the proposed DLCNN initiates the various order of ConvNet filters as given in equation. Algorithm shows the DLCNN procedures in detail.

Algorithm : DLCNN on Image Compression

Input: Image Blocks and Classified Datasets

Output: Training Model for Deep Image Compression and Reconstruction

Begin

Step 1*: Collect the image samples, NEMSVM observations and BTC observations*

Step 2**:**Create a sample size for at least 500 images and at least five features (500*5). Accordingly, Dataset has 2500 features.

Step 3: Find the missing data and noise elements from BTC and NEMSVM observations

Step 4*: Compute ConvNet filters at various orders, 2*2, 4*4, 5*5 and 6*6 depends upon DNN layers that are computed*

Step 5*: Initiate a training agent using image samples, BTC codes and NEMSVM components*

Step 6*: Formulate the DLCNN function as*

$$C^{II} = \sum_{1}^{N} C^M.F^M{}_I \,.\, L.\frac{dt}{ds}$$

Here, L is a DLCNN learning rate.

Step 7*:Determine CNN_M in function and CNN-Max Pooling function*

Step 8*: Determine Image sample functions and Block Scoring function*

Step 9: *Classify Block score based pixel components*
Step 10: *Repeat for all image blocks*
End

Figure illustrates the overall proposed DLDCT techniques and the flow of image compression processes. In addition, this figure provides the interactions of BTC, HMM, NEMSVM and DLCNN modules to implement DLDCT framework. In the flow of the proposed system, BTC is initiated to convert the images in to blocks. In addition, HMM is used to produce both observed and unobserved image contents. In the next phase, NEMSVM classifiers are effectively used to analyze multiple blocks under various threshold conditions. This gives effective classification model. In extend, these results are given to DLCNN layers for producing deep analyzed image observations. These complex procedures deliver more accurate image block analysis for efficient compression and decompression solutions. The proposed DLDCT creates iterative training models for improving the qualities of image compression and decompression rates with minimal MSE and MAE.

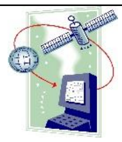
IV. RESULTS AND DISCUSSION

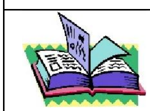
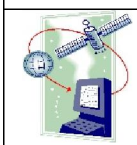
This proposed research work has been implemented with many image collections that are containing standard greyscale images, color images, manipulated database images, scanned book images and different satellite gathering images (SAT images). This implementation platform collects 1026 images from various categories for experimental purpose. In real time, the number of images can be increased.

Table shows the performance comparison of HMM-BTC, AMBTC and proposed DLDCT techniques using various performance metrics for 4*4 image blocks (1026 Images). HMM-BTC and AMBTC produce almost same observations but in terms of quality metric, HMM-BTC gives more details pixels and it increases the efficiency of BTC principles. At the same time, GA-BTC produces more efficient image compression efforts comparing to AMBTC and HMM-BTC. The reason of better GA-BTC is the complex training procedures of GAN networks on BTC implementation.

However, the proposed DLDCT technique creates more supportive results than GA-BTC. Comparing to GA-BTC, the proposed DLDCT works based on multiple CNN units. At the same situation GA-BTC is enabled with only two CNNs (Generator and Differentiator). Tables show the comparisons of implemented techniques. Under all conditions, the proposed system outperform other existing techniques.

Input Image 4 X 4	**Image Name**	**Image Measurements**	**HMM With BTC**	**AMBTC**	**GA-BTC**	**DLDCT**
	Computer	PSNR	39.2	39.12	39.98	40.23
		CR	1.69	1.69	1.98	2.23
		MSE	13.01	13.06	10.78	8.22
		SNR	13.23	12.23	12.54	14.45
		CT	2004	1892	1840	1798
	Database	PSNR	38.12	38.10	38.17	40.22
		CR	1.69	1.70	1.99	2.34
		MSE	13.02	13.09	10.61	8.12
		SNR	12.10	12.21	12.51	14.44
		CT	1905	1899	1872	1822
	Book	PSNR	38.08	38.04	38.14	40.20
		CR	1.73	1.71	1.99	2.38
		MSE	13.01	13.12	10.63	8.08

		SNR	12.33	12.17	12.50	14.44
		CT	2008	1994	1972	1898
	Satellite	ps PSNR	38.02	37.76	38.11	40.20
		CR	1.74	1.72	2.01	2.42
		MSE	13.43	13.78	10.66	8.07
		SNR	12.22	12.02	12.48	14.421
		CT	2134	2146	2098	1979

Input Image 16 X 16	**Image Name**	**Image Measurements**	**HMM With BTC**	**AMBTC**	**GA-BTC**	**DLDCT**
	Computer	PSNR	39.12	39.10	39.94	40.22
		CR	3.73	3.71	4.04	4.22
		MSE	13.09	13.11	10.79	8.11
		SNR	12.43	12.20	12.52	14.34
		CT	1992	1621	1598	1489
	Database	ps PSNR	39.23	39.01	39.91	40.19
		CR	3.78	3.72	4.11	4.23
		MSE	11.55	13.18	10.81	8.11
		SNR	12.03	12.11	12.51	14.32
		CT	1698	1651	1621	1581
	Book	ps PSNR	39.11	38.88	39.89	40.17
		CR	3.79	3.73	4.19	4.32
		MSE	12.66	13.23	10.83	8.08
		SNR	12.12	12.02	12.49	14.33
		CT	1690	1671	1622	1591
	Satellite	ps PSNR	39.01	38.03	39.87	40.17
		CR	3.79	3.76	4.23	4.33
		MSE	12.89	13.33	10.81	8.09
		SNR	12.05	11.88	12.46	14.32
		CT	1756	1722	1696	1605

Input Image 256 X 256	**Image Name**	**Image Measurements**	**HMM With BTC**	**AMBTC**	**GA-BTC**	**DLDCT**
	Computer	PSNR	35.21	34.69	39.29	40.22
		CR	9.11	8.99	10.88	12.22
		MSE	15.12	16.89	13.09	8.03
		SNR	10.11	9.20	12.18	14.11

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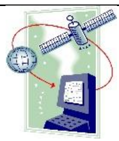
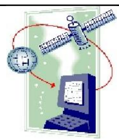
		CT	810	776	765	704
	Database	ps PSNR	35.78	34.71	39.45	40.21
		CR	9.22	9.12	10.90	11.23
		MSE	15.22	16.96	13.11	8.02
		SNR	11.01	9.11	12.16	14.08
		CT	799	778	769	702
	Book	PSNR	35.45	34.66	39.46	40.19
		CR	9.46	9.32	10.90	11.56
		MSE	15.22	16.96	13.11	8.04
		SNR	10.01	9.11	12.16	14.09
		CT	815	781	769	698
	Satellite	ps PSNR	35.12	34.09	39.42	40.17
		CR	9.47	9.37	10.98	11.67
		MSE	14.29	16.99	13.13	8.04
		SNR	10.98	9.04	12.15	14.09
		CT	844	812	797	705

Input Image 512 X 512	Image Name	Image Measurements	HMM With BTC	AMBTC	GA-BTC	DLDCT
	Computer	PSNR	34.92	34.55	39.98	40.12
		CR	9.94	9.23	10.96	11.34
		MSE	13.79	16.99	13.06	8.03
		SNR	10.00	9.03	12.17	14.12
		CT	466	453	436	398
	Database	ps PSNR	37.88	34.43	39.94	40.13
		CR	9.95	9.27	10.99	11.67
		MSE	16.88	17.95	13.16	8.02
		SNR	10.98	9.01	12.14	14.11
		CT	479	467	458	389
	Book	PSNR	37.66	34.25	39.99	40.15
		CR	9.97	9.29	11.98	13.67
		MSE	15.99	17.99	13.13	8.02
		SNR	10.95	8.89	12.12	14.23
		CT	522	472	459	396
	Satellite	ps PSNR	37.23	34.02	40.12	42.56
		CR	9.99	9.39	13.98	14.33
		MSE	17.95	19.99	13.09	8.08
		SNR	10.92	8.78	12.08	14.22
		CT	533	498	481	431

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Our GABTC model produce the images with finer than modified BTC compared smoothing factors and blocking artifacts of the images. It provides the better compression ratio, PSNR values with the modified BTC, for all three data sets, proposed method better and efficient result produces in order to maintain the quality and as well as integrity part of the compressed image. Requires between 21% and 49% more bits than our GC models with CR = 8. These comparisons give the efficiency of proposed DGAN system in terms of minimal MSE and optimal computation time for various image blocks.

Input Images	No. of Images	Image Measurements	BTC	AMBTC	KBTC	Proposed Method
512X512	500	Average CR	1.76	1.81	1.84	1.91
		Time Calculation (Time Taken)	1526	1490	1459	1431

Table 6: Average Performance of Various Image Compression Techniques

Table 6 gives the maximum block size efficiency rate of BTC, AMBTC, KBTC and proposed DGAN approaches for 500 images. In this comparison, DGAN generates little overhead in time but gives better compression ratio.

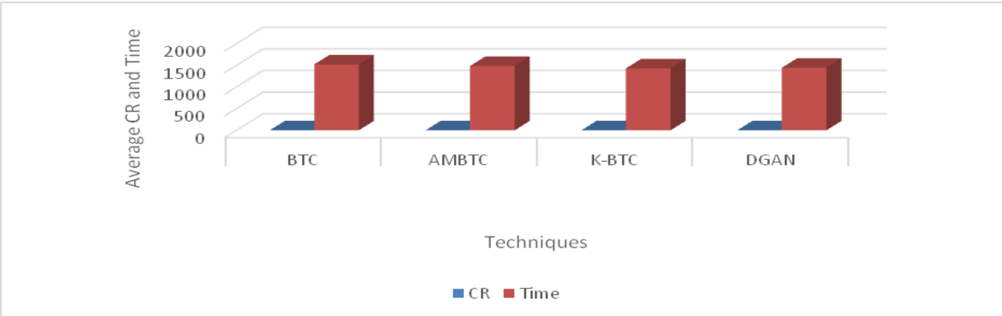

Figure 6. Average Performance of various Techniques

Figure 7. PSNR of various Techniques for 512B Image Blocks

Figure give the comparison of BTC, AMBTC, KBTC and GA-BTC-DGAN for compression ratio, Computation time and PSNR parameters. In the same manner, figure shows the details of MSE based technical comparison. In this comparison, the proposed technique provides minimal MSE compared to other techniques.

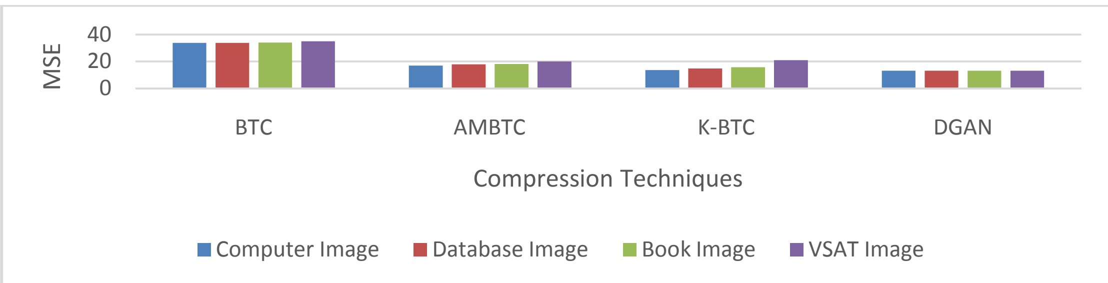

Figure 8 MSE of various Techniques for 512B Image Blocks

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A GAN-primarily based totally framework for learned generative compression, and provided the primary thorough study of such a framework for full-resolution picture compression. Our results show that for low bitrates, such Generative Compression (GC) can provide dramatic bitrate financial savings compared to preceding latest strategies optimized for classical targets which include MS-SSIM and MSE, when evaluated in phrases of visible quality in a consumer study. Furthermore, we tested that constraining the utility area to road scene pix results in extra garage financial savings, and explored (for SC) selectively combining completely synthesized picture contents with preserved ones when semantic label maps are available. Interesting instructions for future paintings are to broaden a mechanism for controlling spatial allocation of bits for GC (e.g., to achieve better preservation of faces; possibly using semantic label maps), and to mix SC with saliency information to determine what regions to preserve.

In the comparisons given in above tables, the proposed DLDCT provides more dependable results over various types of image blocks. Even though the proposed DLDCT gives little computation overhead comparing to other techniques, it is negligible under recent computer technologies. This proposed system produces minimal MSE and effective compression ratio for various image types.

Input Images	No. of Images	Image Measurements	HMM With BTC	AMBTC	GA-BTC	DLDCT
512*512	500	Average CR	1.80	1.81	1.91	1.99
		Time Calculation (Time Taken)	1511	1490	1431	1412
512*512	1026	Average CR	1.84	1.89	2.15	2.34
		Time Calculation (Time Taken)	1987	1973	1898	1801

Table 7. Overall performance and Comparison

The proposed DLDCT is not strictly following the relationships between various performance metrics. The reason is this technique increases the efficiency and reduces the MSE based on effective training procedures. As the number of layers in DLCNN increases, the accuracy of the proposed system initiates for better compression ratio and minimal MSE rates.

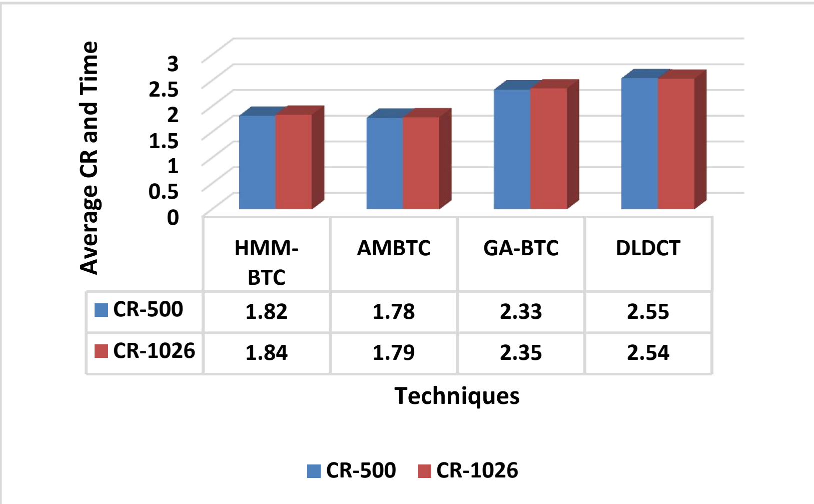

Figure 9 Average Performance of various Techniques for CR

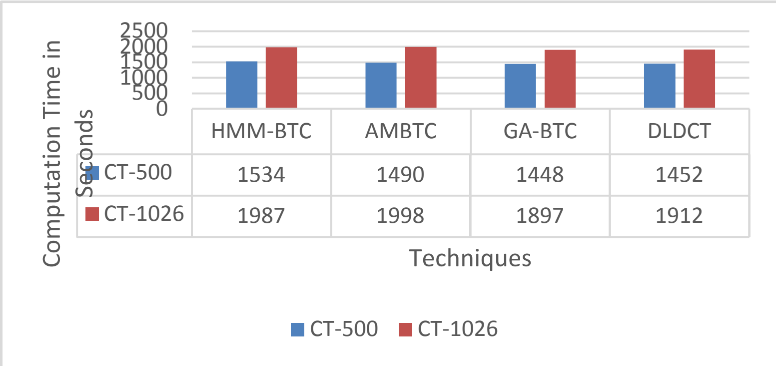

Figure 10 Average Performance of various Techniques for CT

Figure 11 PSNR of various Techniques for 512B Image Blocks

Above Figures illustrate the performances of proposed technique and existing techniques in terms of CR (for 500 images and 1026 images) and CT (for 500 images and 1026 images). They are illustrated as CR-500, CR-1026, CT-500 and CT-1026 respectively.

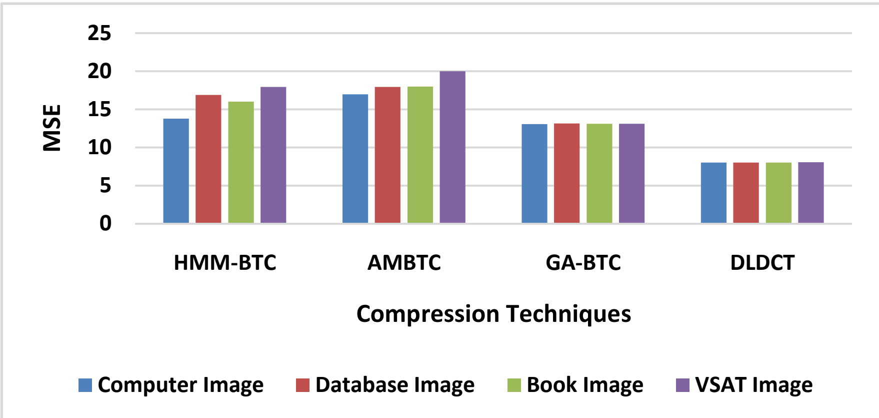

Figure 12 MSE of various Techniques for 512B Image Blocks

Above figures shows the collective performances of all image compression techniques based on CR, CT, PSNR and MSE. These figures are mainly showing the benefit of using proposed DLDCT techniques over other techniques.

In this paper, DGAN (GA-BTC) based image compression and reconstruction techniques were proposed for e-learning images. This system dealt with most complicated images and heterogeneous images of e-learning systems. This proposed technique had been modelled with deeply trained DNNs and image training sets. In this work, the proposed DGAN was implemented and compared with BTC, AMBTC and KBTC techniques. In the comparison, the proposed DGAN worked well with optimal performance metrics. This work shall be implemented for more images and other multimedia resource compression strategies in future. Final methodology of image compression in E-learning environment will be discuss ie Dual Layered Deep Classification and Truncation (DLDCT) technique.

Image compression and decompression are inevitable techniques in any E-learning systems. E-Learning systems are mainly depending on image databases. This proposed technique concentrated on finding the difficulties and optimizations in image compression techniques. In tis regard, the proposed DLDCT technique and the supportive DL approaches were implemented to get more accurate pixel analysis models and reconstructing model. The proposed DLDCT created an effective image compression and analysis training model to improve quality of image compression. In the same manner, this technique helped to develop iterative image compression models. The performance of proposed technique was noted and compared with existing systems. From the deep practical analysis, it was noted that the proposed technique delivered more effective results.

V. CONCLUSION

This paper describes three main areas concerning the efficient storage of images in the E-learning environment. First main area is Generative Adversarial Block Truncation Coding Technique for improving Block Constructions. The final area is Multi-Classifiers and Deep CNNs method for best compression method to storage the images in the E-learning storage environment and calculated important parameters to decompress the image with quality and also results compared with existing methodologies. Modified Block Truncation Coding algorithms are showing better compression and quality image ratio in the cloud environment for storing large amount of data efficiently. It can also be extended for compressing 3-D images, by dividing images into suitable basic cube blocks of pixels.

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