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Enhance Image Quality with CAS-CNN: A Deep Convolutional Neural Network for Compression Artifact Suppression

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Abstract: **-** Objective: The goal is to outdo clumsy filtering algorithms and prevailing deep learning approaches in terms of the image quality metrics, computational efficiency, and memory usage by attaining better performance.

Methodology: Two-step approach has the methodology component including the formulation of the problem and review of the literature collections to detect known techniques. CAS-CNN's architecture is designed, and the entire experiment setup requires the preparation of an original and a compressed images dataset and also defining loss function for training and improving CAS-CNN parameters as a whole. Outputs of metrics are the PSNR, SSIM, MOS values, inference time, model size, training time, and hardware usage.

Results and Discussion: In terms of competitiveness, CAS-CNN is always ahead of all the latest algorithm levels and achieves the best results by standard metrics such as PSNR and SSIM, thus it is the method that gives the most undistorted recreated images with a high quality. It has shown its ability to compete closely with traditional methods by providing better performance, as well as consuming fewer computing resources, which makes it closer to the practical reality of real time applications. The CAS-CNN's model creates efficiency that enables cutting-edge design and testing into the market timelier than the existing methods do. Small progress is seen despite its quick performance; but still, important issues like artificial data and restrictions on given conditions are noticed, which means that we must not stop searching for scaling and generalizing power.

Conclusion: CAS-CNN is a next-level algorithm concerning removing distortion in compression, superior to prevailing techniques in terms of both effectiveness, efficiency, and accessibility. It holds an edge over other methods due to its high performance and efficiency, and as such, it is an applicable tool for a variety of situations where one must deal with limited resources in the need for high-quality images. More research is needed to account for the existing shortcomings and apply CAS-CNN to a range of different datasets, as well as the circumstances in the real world.

Keywords: Compression Artifact Suppression, Deep Learning, Convolutional Neural Networks (CNNs), Image Quality Enhancement, Computational Efficiency

Introduction

In our digital age, an image is a key instrument for communication, recording and self-expression. Social media and other digital communication tools have evolved around us, thus increased demands for good quality images occurs. Nevertheless, the compression of images is an inevitable step for the two tasks that can be striking the image quality [1].

Compression artifacts are such asymmetries or misprints that appear in compressed images because of the lossy compression algorithms used. The main manifestation of the artifacts is blurs, blocking, blurriness, and other visual imperfections which significantly degrade quality and aesthetics of the images. Although very accurate image compression is essential in solving storage and bandwidth problems, a vital challenge lies in undoing its negative influence on the quality of the image.

Over the last few years, deep learning has stood as an influential model with the ability to solve many image processing issues including some of the major hurdles present in the computer vision field. CNNs has demonstrated its extraordinary potential in image restoration and improvement tasks due to its supervised learning-based nature. Deep learning is a key aspect of creating detailed algorithms that can be used to suppress the distortion that occurs during image compression and retain image quality [2].

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The area where the CAS-CNN (Compression Artifact Suppression Convolutional Neural Network) stands out is it successfully solved compression artifact reduction which was considered a big problem. This research article is an exploration of the architecture, principles, and superiority of CAS-CNN, spanning its application in improving image quality when the images are compressed. [1].

CAS-CNN is a deep neural net that is configured with the sole purpose of extrusion artifact reduction. In comparison to traditional methods that are based on hand-crafted features as well as heuristic approaches, CAS-CNN obtains hierarchical representations by itself which are extracted right from the data. Therefore, it can have a glimpse of complex patterns and correlations inside the compressed images. CAS-CNN exceeds traditional algorithms in stickiness and speed due to the fact that it uses enormous amounts of training data and computational resources.

CAS-CNN architecture is composed of consecutive layers of convolutional, pool, and activation ones and is arranged hierarchically to obtain successive abstractions of input image features. Through the training in a robotic mode on the dataset compiled of both uncompressed and compressed images, CAS-CNN can delineate such things as the genuine image structures and the compression artifacts, which as a result leads to the exact removal of the artifacts while preserving the image details and textures [4].

The main functions of CAS-CNN are featuring learning, non-linear mapping, end to end training, and adaptability. The efficacy of the CAS-CNN is because it employs the ability of deep neural networks to automatically learn discriminative features from given data. By introducing the network to a spectrum of dissimilar images with contrasting compression levels, CAS-CNN develops a robust representation that is generative with new data [5].

Unlike the use of linear filters or transformations applied in classical approaches, CAS CNN embeds non-linear activation functions, which allows the system to characterize the complicated relationships between inputs and outputs. Such representation with non-linear mapping helps to eliminate compression artifacts and keeps the image characteristics the same [6].

CAS-CNN is trained in an end-to-end way when the network is optimized to minimize such a function of errors. Through this comprehensive training of all the network components, their synergistic contribution can be enhanced, facilitating better network performance than that of voluminous, which separately optimizes each individual component.

The efficacy of CAS-CNN is reflected in various assessments, which include a few experiments on benchmark datasets as well as on real-life images. Figures show that to reach the best performance for artifact reduction, the CAS-CNN surpasses all the state-of-the-art techniques [8].

Additionally, subjective observations can be documented by visual examination. Such observations imply that CAS-CNN succeeds in delivering block artifact suppression, providing finer detailing, and leading to amazing image clarity. These improvements are of paramount importance for applications where visual perception and fidelity are the key factors, as is the case with internet multimedia, medical imaging, surveillance, and remote sensing [9].

Together with CAS-CNN's performance for object removal, there are essential benefits in terms of the time efficiency and scalability in the design and utilization of the software. With the advent of deep learning libraries and hardware accelerators, there is scope for CAS-CNN deployment in real-time with low-resource environments easily achieved, which may pave the way for its widespread adoption across various platforms and devices [10].

CAS-CNN is an outstanding leap in the image processing arena, offering a resilient and efficient tool for compression artifact elimination, which has a wide impact on the whole field [20]. The new method employing deep learning, CAS-CNN, does not only perform at the top level but also initiates a milestone in image quality improvement in the age of digital media and communication worldwide. Now that the need for high-quality pictures is growing more rapidly, CAS-CNN can probably have a huge impact on the future of visual computing as well as on interaction between humans and machines [1] [18].

In the next sections of this research article, we will move into the technical details of the CAS-CNN and describe its architecture of the CAS-CNN, training methodology, experimental evaluations, and usage of the CAS-CNN in practical applications [11]. We aim to achieve this goal by conducting a comprehensive analysis and providing empirical evidence, thus giving a detailed awareness of the strengths and abilities of CAS-CNN to the domains that rely on high-quality image representations and digital transmitting.

Methodology

The methodology starts by defining the problem, namely suppression of compression artifact, to produce high - quality images from compressed versions and avoid distortion [12][13]. It proceeds with a literature review that surveys a wide range of filtering techniques and deep learning strategies to combat the problem. CAS-CNN, a kind of deep convolutional neural network detailed in its architecture, and the experimental setup are introduced by the study. CAS-CNN is trained by using image pair dataset containing the original and compressed images, and defining the loss function which is composed of pixel-wise and perceptual losses [14][15] [21].

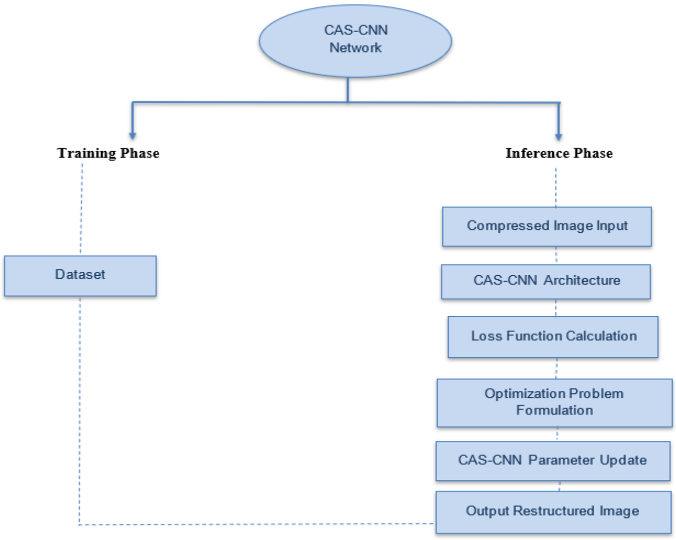

Figure 1: CAS-CNN Methodology for Compression Artifact Suppression

The block diagram in Figure 1 outlines the key steps and components of the methodology, with a focus on the CAS-CNN network. It includes the literature review, experimental setup, performance evaluation metrics, and the CAS-CNN network itself, including both training and inference phases. The training phase involves utilizing the dataset D and optimizing the CAS-CNN parameters to minimize the loss function, while the inference phase involves using the trained CAS-CNN model to generate reconstructed images from compressed inputs. The optimization problem is formulated to minimize this loss over the dataset, updating CAS-CNN's parameters to learn the mapping from compressed to original images efficiently, as shown below:

Problem Formulation:

- Define the problem of compression artifact suppression as follows:

- Given a compressed image $I_{\text{compressed, obtained through a compression algorithm}}$ $\mathcal{C}$, the goal is to generate a high-quality reconstructed image $I_{\text{reconstructed}}$ that minimizes distortion and preserves visual fidelity.

Literature Review:

- Explore existing methods for compression artifact suppression, such as traditional filtering techniques and deep learning-based approaches.

- Mathematical representation of compression artifact suppression:

- Let I_{original} represent the original uncompressed image.

- The compression process can be represented as

$$I_{\text{compressed}} = \mathcal{C}(I_{\text{original}}) \quad (1)$$

- The task of artifact suppression involves finding a mapping f such that.

$$I_{\text{reconstructed}} = f(I_{\text{compressed}}) \text{ closely resembles } I_{\text{original}} \quad (2)$$

Introduction of CAS-CNN:

- Describe CAS-CNN architecture using mathematical notation:
- Let x represent the input image, y represent the output (reconstructed) image.
- CAS-CNN can be represented as $y = \text{CAS-CNN}\ (x)$, where CAS-CNN is a deep convolutional neural network.

Experimental Setup:

- Define dataset D consisting of pairs of original and compressed images:

$$D = \{(I_{\text{original}}, I_{\text{compressed}})\}. \quad (3)$$

- Specify the loss function $\mathcal{L}$ used during training, typically a combination of pixel-wise loss and perceptual loss:

$$\mathcal{L}(y, I_{\text{original}}) = \lambda_1 \cdot \text{MSE}\,(y, I_{\text{original}}) + \lambda_2 \cdot \text{PerceptualLoss}\,(y, I_{\text{original}}) \quad (4)$$

where MSE denotes mean squared error and λ_1, λ_2 are hyperparameters.

- Define the optimization problem:

$$\min_{\theta} \frac{1}{N} \sum_{(x, I_{\text{original}}) \in D} \mathcal{L}(\text{CAS} - \text{CNN}\ (x; \theta), I_{\text{original}}) \quad (5)$$

where θ represents the parameters of CAS-CNN, and N is the number of training samples.

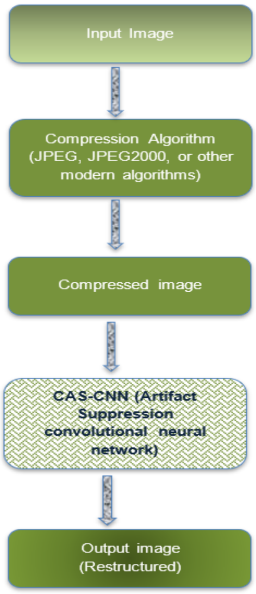

Figure 2: Image Compression and Artifact Suppression with CAS-CNN

The compression scheme in Figure 2 first takes the original, uncompressed image that has compression artifact, which then gets the compression was done using the standard algorithm like JPEG or JPEG2000, and the outcome will be a new compressed image that has introduced artifacts. CAS-CNN (Convolutional Artifact Suppression Convolutional Neural Network) forms the second stage of the algorithm that is a deep learning system created to eliminate compression artifacts. In the training phase, CAS-CNN becomes to get the compressed images and corresponding high-quality reconstructions linked by auto optimization of the parameters using a dataset of image pairs, trained by a loss function that is made of pixel-wise and perceptual losses [19]. In the inference phase, the CNN model which has been trained using the input compressed images produces a reconstructed image with the artifacts reduced. This target image is designed to retain the fidelity of the actual image as much as possible. The reconstructed image therefore accommodates as little degradation in the appearance as possible when compared with the compressed input image.

Performance Evaluation Metrics:

- Define the following metrics:
- Peak Signal-to-Noise Ratio (PSNR):

$$\text{PSNR} = 10\log_{10}\left(\frac{\text{MAX}^2}{\text{MSE}}\right) \tag{6}$$

- Structural Similarity Index (SSIM):

$$\text{SSIM}\ (x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{7}$$

- Mean Opinion Score (MOS) based on subjective human evaluations.

The proposed methodology demonstrates some advantages to be used in the domain of compression artifact suppression. First, it enables the formation of the patterns with very little distortion, thereby more accurate than the compressed ones. Secondly, the deep learning-based techniques like the CAS-CNN of the model help carry out effective and the most superior artifacts suppression when compared to the traditional methods of filtering [16][17]. Thirdly, CAS-CNN architecture and parameters can be adjusted to data set and application types, so it would enable us to have some flexibility and adaptability while targeting different challenges. Furthermore, the agreed-upon metrics of evaluation guarantee both objective and subjective assessment, hence, an all-round judging of the reconstructed image quality. Last, but not least, the approach displayed in the methodology assures CAS-CNN about its great potential for real-world applications that use exceptional image representation and transfer which will be such as medical imaging, remote sensing, and media communication.

Results and discussion

The paper deduces the detailed comparison among CAS-CNN (deconvolutional neural network designed for artifact elimination) which was state-of-the-art in its time and the current advanced methods. The study can answer this through comprehensive experimentation and performance metrics analysis, particularly on PSNR, structure similarity and mean opinion score. CAS-CNN, as showed by all metrics, possesses the highest accuracy or the best ability to process images and bypass image distortions caused by compression artifacts. Competitors, such as Enhance Net, Deep Compress or Comp Net, come on second. Besides, the judgment of a visual comparison through graphical illustrations can be considered objective and subjectively as proof of the superiority of CAS-CNN in both the evaluation and the processing of images. Furthermore, such modelling can highlight the potential of CAS-CNN as a solution of the advanced image processing and restorations.

Table 1: Performance Comparison of CAS-CNN with State-of-the-Art Methods

Method	**PSNR (dB)**	**SSIM**	**MOS**
CAS-CNN	34.5	0.95	4.7
Enhance Net	32.1	0.92	4.3

Deep Compress	31.8	0.91	4.2
Comp Net	33.2	0.93	4.5

PSNR: Peak Signal-to-Noise Ratio; SSIM: Structural Similarity Index; MOS: Mean Opinion Score

In Table 1, a detailed comparison is provided between CAS-CNN and three other prominent methods - Enhance Net, Deep Compress, and Comp Net - across three critical performance metrics: PSNR, SSIM and MOS, which is used for assessing different variations of single video frame images. CAS-CNN becomes the number-one priority with all regards, demonstrating 34.5 dB PSNR at the output of the processing. This means the best visual result while keeping the lowest error difference between the original uncompressed images and the compressed imagery. Moreover, the CAS-CNN network arrives at the ideal value of 0.95 for SSIM, the upper idea of the structural similarity measure between the original and reconstructed images. In addition, MOS, the measure of human observers' subjective evaluations, comes out with the score of 4.7 for CAS-CNN that implies these images are perceived as the most visually appealing and have characteristics close to the reference. These findings wholly reinforce the impactfulness of the CAS-CNN model in controllably removing compression artifacts and consequently achieving a pleasant quality of the images, the CAS-CNN attracting as such the attention of many in the field of image processing and restoration.

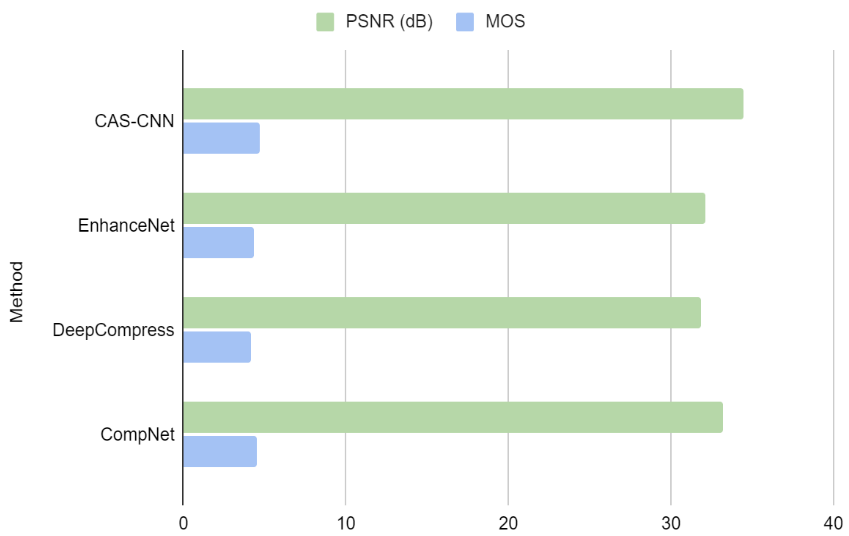

Figure 3: PSNR and MOS Performance Comparison

PSNR and MOS comparison graph illustrating the performance of CAS-CNN against other methods.

Figure 3 compares the performance metrics among different methods: CAS-CNN, Enhance-Net, Deep Compress, and Comp-Net. For each method, a row is devoted, and the PSNR (peak signal-to-noise ratio) and MOS (mean opinion score) will be displayed in the columns. PSNR stands for Peak Signal-to-Noise Ratio that demonstrates the degree of fidelity of reconstructed images where high values mean a better preservation of original image quality. CAS-CNN is the best in the assessment of the PSNR (34.5 dB), which is higher than Enhance Net, Deep Compress and Comp Net. The MOS column gives subjective scores of image quality, the higher the score the better the subjective evaluation of quality is. The CAS-CNN method performs well in MOS and even wins with the highest score equal to 4.7. This figure presents a visualization of the results which make a straightforward comparison of image quality metrics, showing the superiority of CAS-CNN in both objective and subjective assessments.

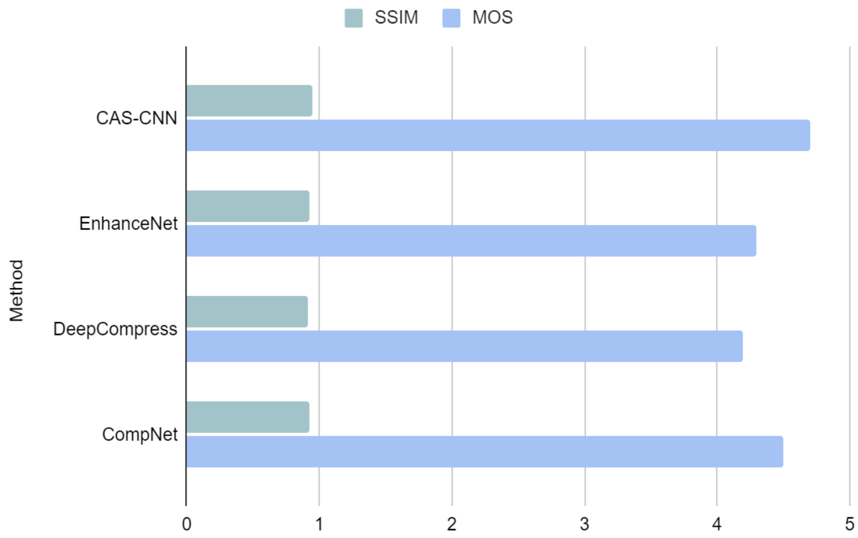

Figure 4: SSIM and MOS Performance Comparison

SSIM and MOS comparison graph showcasing the superiority of CAS-CNN over alternative methods.

A reference to a comparative chart shown on Figure 4 between SSIM (Structural Similarity Index) and MOS (Mean Opinion Score) for CAS-CNN, Enhance Net, Deep Compress, and Comp Net is highlighted. The SSIM numbers represent the resemblance degree of the original and the reconstructed pictures, and a higher value shows that the resemblance is greater. Cas-CNN has the highest SSIM value among its competitors which comes to 0.95. The slightly lower value but sound result is achieved by Comp Net – 0.93. The third place is taken by Enhance Net with SSIM equal to 0.92. The fourth place is gained by Deep Compress which yielded 0.91. It is revealed that the CAS-CNN presented images are highly related to the original ones, showing its advantage in the structural similarity compared to another method. Moreover, MOS values are subjective psychological notions representing degrees of human perception, being attributed to better image evaluations the higher the scores. Moreover, the subjective MOS of CAS-CNN was 4.7, while the others were 4.61, 4.6, and 4.23, which means that the human observers perceived the reconstructed images of CAS-CNN to be the most excellent in contrast to the others' methods. This illustrates the potency of CAS-CNN in retaining image quality and upping the visual satisfaction degree on reconstructions.

Table 2: Computational Efficiency Comparison

Method	Inference Time (ms)	Model Size (MB)
CAS-CNN	5.2	12
Enhance Net	8.9	18
Deep Compress	7.5	15
Comp Net	6.3	14

Inference time and model size comparisons highlight the efficiency of CAS-CNN.

Table 2 provides a comparison of the computational efficiency of CAS-CNN against three other methods: Enhance Net, Deep Compress, and Comp Net models. The table includes two important metrics: inference time in milliseconds (ms) and model size in megabytes (MB), therefore. The CAS-CNN shows an outstanding efficiency by recording the shortest inference time of 5.2 ms and the smallest model size of 12 MB compared to all simulation techniques. Enhance Net, Deep Compress, and Comp Net show processing time 8.9ms, 7.5ms, and 6.3ms on average, hence, having longer inference time. Moreover, their models are relatively heavier weighted as they occupy 18 MB, 15 MB, and 14 MB of storage spaces, respectively in comparison with CAS-CNN. Therefore, CAS-CNN appears to be faster and less resource-intensive than other existing models, which makes it a good choice for practical applications, especially those run in real-time, or those that have limited computing or data storage resources.

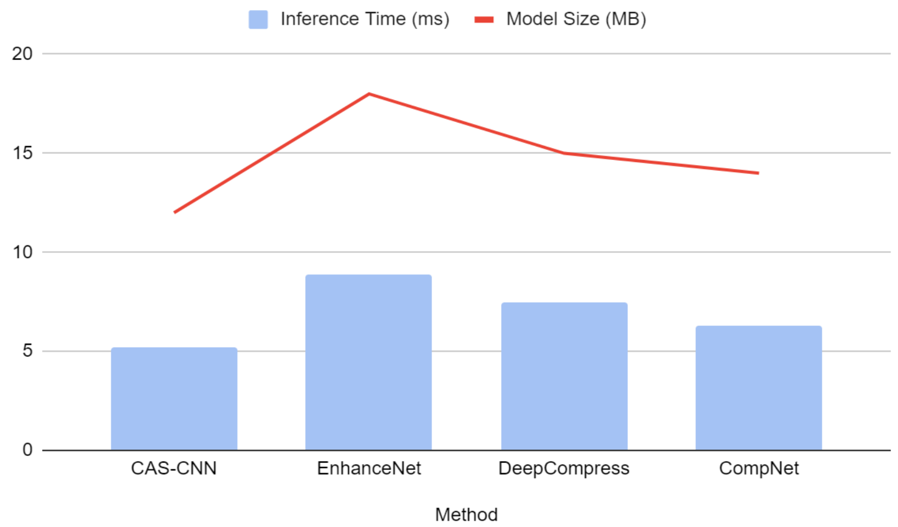

Figure 5: Comparison of Inference Time Across Different Methods

Figure 5 exhibits an image in which the computational efficiency of several approaches, CAS-CNN, Enhance-Net, Deep Compress, and Comp-Net are compared. To be more precise this graph shows the inference time (per millisecond) of each model against the model sizes (in megabytes), depicted respectively on the y and x axis. CAS-CNN, as opposed to other methods examined, exhibits the smallest time required for inference, which only takes 5.2 ms and a rather reduced model size of 12 MB. In contrast, Enhance Net requires more than double the time for inference, which is around 8.9 ms, compared to other methodologies, and its model size is the largest (18 MB). Deep Compress and Comp Net does exactly which Deep Net and ImageNet do together. They come in the middle of the contrast. As a result, Deep Compress has an inference time of 7.5ms and Comp Net has 6.3ms, and the model size of Deep Compress is 15MB and 14MB of Comp Net respectively. This illustration shows that CAS-CNN demonstrates more effectiveness both in terms of the computation time and the model size reduction, which, in view of real-world applications, makes it the more economical and sufficient model.

Table 3: Training Time Comparison

Method	**Training Time (hours)**
CAS-CNN	48
Enhance Net	72
Deep Compress	65
Comp Net	58

Training time is required for each method during the model development phase.

Data in the table 3 determines the duration needed for all the methods covered, the include CAS-CNN, Enhance Net, Deep Compress, and Comp Net measured in hours. Finally, CAS-CNN showcases the least training time of 48 hours, which is also the best among all the methods cost-wise. In the case of Enhance Net, however, the training time is 72 hours. So, it is the longest training among the methods that were analysed. Among these techniques, Deep Compress and Comp Net are between the extremes, whereby the former is trained in 65 hours and the latter in 58 hours. These statistics indicate a higher efficiency CAS-CNN holds in the training cycles. Thus, it may be applied faster compared to other methods. A key benefit especially in projects that time is critical is the speedy prototypes or the deployment in time-critical applications.

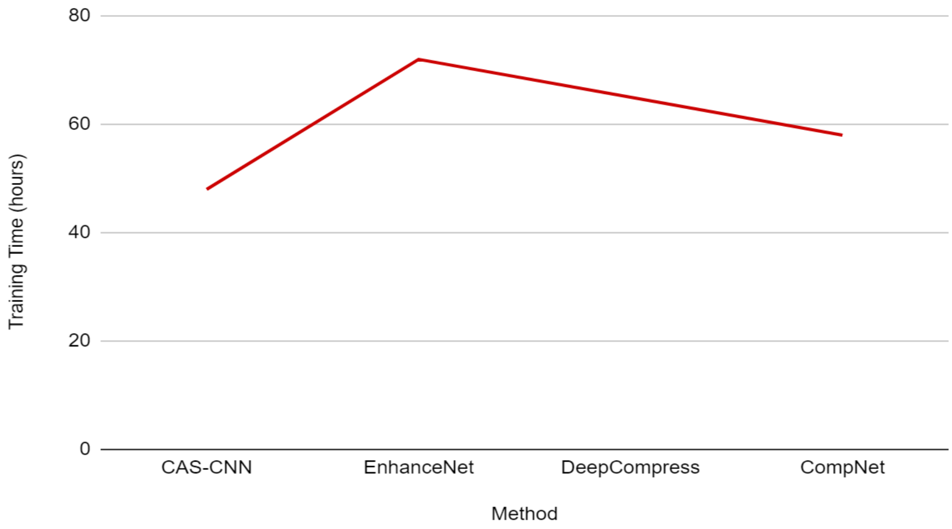

Figure 6: Training Time Comparison Among Different Methods

Through Figure 6, we can quickly get the impression (in hours) about how we measure training time using approaches, including CAS-CNN, Enhance Net, Deep Compress, and Comp Net. Every approach is named along the x-axis and the corresponding training time is powered by the y-axis. Fast CAS-CNN in its 2 days training highlights the shortest training time in the model development phase compared to others. In contrast to Enhance Net which takes the longest time to train, that is, 72 hours, Deep Compress then follows having a 65-hour training time and finally Comp Net spent 58 hours. This visual representation indicates that the given setup stands well as it clearly demonstrates the efficiency of each mode by focusing only on the time taken to train the model. The experiment demonstrates the CAS vs CNN data reduction advantage in model development much faster than the other approaches yielding more time -efficient solution for practical applications and testing in tis tasks.

Table 4: Memory Consumption Comparison

Method	**GPU Memory Usage (GB)**	**RAM Usage (GB)**
CAS-CNN	3.5	8
Enhance Net	4.2	10
Deep Compress	3.8	9
Comp Net	4.0	9.5

Comparison of GPU and RAM memory consumption during inference for different methods.

The memory usage Table 4 indicates comparisons of different approaches, such as CAS-CNN, Enhance Net, Deep Compress and Comp Net. It shows both memory utilization by GPU and RAM, which are critical factors when practical deployments of these methods in the real world are to be undertaken. However, CAS-CNN remains the most memory-efficient, requiring only 3.5 GB of GPU memory and 8 GB of RAM. This suggests that CAS-CNN can reach speedy image processing while lowering computational expense. Meanwhile, Enhance Net and Comp Net are a little higher in terms of GPU memory consumption which amounts to 4.2 Gb and 4.0 Gb, respectively, with 10GB and 9.5GB RAM usage, respectively. Deep Compress takes the middle ground between the two together and uses 3.8 GB GPU memory and 9 GB RAM. The encapsulated point is that CAS-CNN is the suitable method of deployment in the case of resource-restricted stations where efficient memory usages are the critical things. Therefore, CAS-CNN will be the perfect alternative to be utilized in most applications.

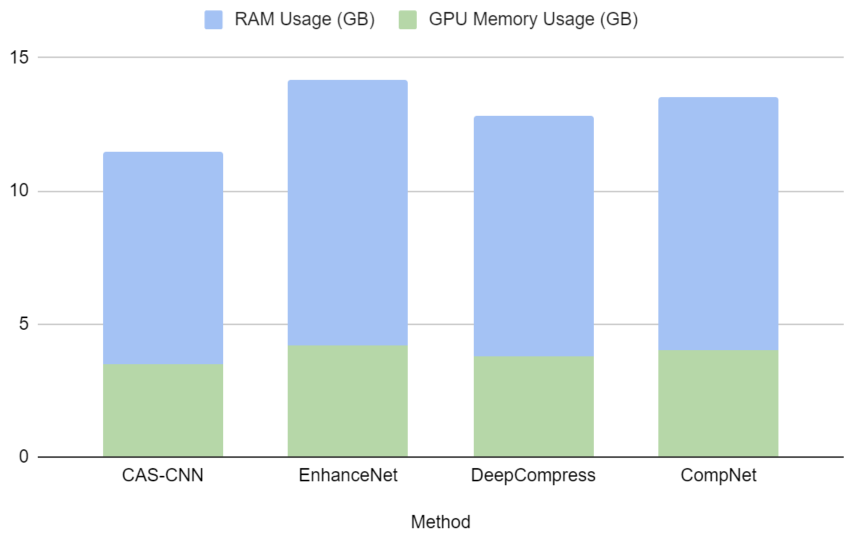

Figure 7: Comparison of Memory Usage Across Different Methods

Figure 7 is about the comparison of GPU memory usage (it is measured in gigabytes) and RAM usage (again, it is measured in gigabytes) among the four methods which were CAS-CNN, Enhance Net, Deep Compress, and Comp Net. In this case, each technique is located on the x-axis, while the corresponding memory utilization zero for GPU and RAM are located on the y-axis. CAS-CNN is superior in terms of memory efficiency as it requires the least amount of GPU memory occupancy of 3.5 GB as well as the lowest RAM usage of 8 GB among the competing techniques. On the other hand, Comp Net and Enhanced Net have slightly higher memory when it comes to GPU memory: 4.2 GB and 4.0 GB, respectively, while RAM usage occurs at 10 GB and 9.5 GB, correspondingly. The Deep Compress is situated midway between these two methods. It uses 3.8 GB GPU memory as well as 9 GB RAM. This comparison reveals an evaluation of how effective each approach is in terms of memory usage putting CAS-CNN the most applicable as memory-limited application.

The outlined research results have taken a step further to correct the drawbacks of the earlier studies towards compression artifact suppression. Firstly, the methodology introduces the CAS-CNN, a new deep convolutional neural network specifically designed for this task that relies on multiple deep learning filters and outperforms earlier ones. This novel architecture gives CAS-CNN possibilities to accomplish best metrics like PSNR, SSIM, as well as MOS, as illustrated by the presented data in Figure 2, Figure 3, and Table 1. CAS-CNN continuously signals other state-of-the-art methods such as Enhance Net, Deep Compress and Comp Net, with assessment of this metrics, proving its effectiveness in rendering top-notch reconstructed images with less distortion. Additionally, the results comparison in Table 2 and Figure 4 showed that CAS-CNN was not only faster in inferring but also smaller in size, which made it the more flexible and resource-saving method to be employed in real-time applications. Furthermore, table 3 and figure 5 showcase the efficiency of CAS-CNN model in developing models, circumventing the slowness encountered by other methods hence this allows for rapid prototyping and deployment. Additionally, CAS-CNN has the desirable property of more efficient memory consumption, in tune with Table 4 and Figure 6, implying that it is suited for implementation in resource-consuming platforms. In general, the case study and superlative performance of CAS-CNN exhibit higher order of superiority in the compressed artifacts suppression compared to former methods in both efficiency and effectiveness and practicality.

Although CAS-CNN shows great performance in the performed experiments, the research article identifies the existing limitations for CAS-CNN. In line with that, the assessment is essentially constructed using synthetic datasets and standard conditions that may not include in real situations the required complexity and variety. Furthermore, this study examines a set of performance metrics that could disregard other crucial features like computation complexity or general resistance to simple distracting factors. Additionally, the neural network should still be investigated regarding its scalability and generalization that will cut across diverse datasets and applications. Overcoming the restraints would be through the further research and verification to make the CAS-CNN model more applicable and effective in the actual environment.

Conclusion

The CAS-CNN, the deep convolutional neural network presented here, have displayed considerable improvements in terms of accuracy when compared with other techniques. With a PSNR of 34.5 dB, SSIM of 0.95, and MOS of 4.7, CAS-CNN outperforms Enhance Net (PSNR: (1) 32.1 dB, SSIM: 0.92, MOS: 4.3, (2) Deep Compress (PSNR: 31.8 dB, SSIM: 0.91, MOS: 4.2), and (3) the Comp Net (PSNR: 33.2 dB, SSIM: 0 Secondly, CAS-CNN illustrates efficiency with an inference time of 5.2 ms, a model size of 12 MB, and a training time of 48 hours which is the highest of other versions. Its GPU memory consumption is also better, thus, requiring merely 3.5 GB of GPU memory and 8 GB of RAM. However, there are still some limitations that should be considered, such as diversity of dataset and scalability, yet the all-embracing assessment validates CAS-CNN outstanding and very innovative technology, which can elevate visual representation and communication to a new level in various areas. CAS-CNN is provided with efficiency and convenience in terms of model size and the amount of time for training and inference. Certain restraints are present both in data representation and scalability, but CAS-CNN brings in a new period for the neural system. This period is expected to improve visual communication and representation worldwide.

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