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JPEG Artifacts Removal using Deep Residual Autoencoder

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ABSTRACT: In the modern era, an enormous amount of data is being generated on a daily basis. Compression techniques are widely used to store data in the most efficient way with the minimum storage space possible. JPEG is a very popular standard image format for lossy and compressed data. Due to its lossy nature, several artifacts such as blocking, ringing, etc. get introduced during compression. To overcome this drawback, we propose a model for JPEG artifact removal using a deep residual autoencoder. The proposed method generalizes the process of JPEG artifacts restoration and restores the quality of compressed image for lower compression levels. This method restores compressed images in YCbCr colour space. Among these 3 channels, Y-channel is the only dominant channel comprised of most information, while the CbCr channels represents colour difference information. This reduces model training time. To reconstruct Y-channel and CbCr channel, two separate autoencoder based models are trained. This model incorporates Residual-in-Residual Dense Blocks(RRDB), which enhances feature learning and overcomes the problem of vanishing gradient using skip connection architecture. The dataset used for testing is LIVE1 and by comparing the PSNR and SSIM quality metrics of the proposed technique to those of previous restoration models, its performance is assessed. The model is trained using the DIV2K dataset. Our proposed method achieves 5.23%, 1.6% rise in SSIM in comparison with AR-CNN and Simone Zini et al. model respectively even with much less computational complexity.

KEYWORDS: Autoencoder, Residual Learning, JPEG compression, Residual-in-Residual Dense Blocks, skip connection architecture

I. INTRODUCTION

JPEG (Joint Photographic Expert Group) is a popular standard image format for lossy and compressed image data. In the modern era, where enormous data are being generated, there is an immense need of compressing data. So, JPEG compression is widely used as a favoured compression technique. Compression methods like JPEG are essential for preserving storage and bandwidth for the transmission of numerous images. There are two types of image compression algorithms: one is lossless image compression, which is particularly used in applications where preserving every detail and pixel accuracy is crucial. For example, in medical imaging. The second approach utilizes a less precise image compression technique, enabling greater compression ratios, while introducing a degree of distortion in the resulting image. It is a widely used compression standard in photography. JPEG compression comes under the lossy image compression category, which allows the user to store the image file with desired compression levels called "Quality Factor" which can range from 1 to 100, where 1 is a quality factor which implies a very high compression to an image.

JPEG compression algorithm transforms the colour image from RGB to YCbCr colour space, then performs further processing. Changes in luminance are more perceptible to the human visual system than changes in chrominance, chroma components (CbCr) can be highly compressed without significantly degrading the visual quality of the image. In JPEG compression, values in the quantization table determines the level of compression. Higher the values in the quantization table, greater the loss of image quality and vice-versa. [1] gives a detailed explanation regarding JPEG compression process.

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During JPEG compression, various kinds of artifacts such as, blocking, ringing, etc. can be introduced due to the lossy nature of the compression algorithm. The presence of these artifacts degrades the quality of an image and negatively impacts the viewer's experience, which makes it difficult to use these images in some critical applications where sharp image quality is crucial, such as in medical imaging, in computer vision applications.

Several JPEG restoration strategies have been put forth in recent years to preserve important details and enhance the visual appeal of images. Along with traditional image processing techniques[2-4] for the restoration of compressed JPEG images many deep learning-based studies[5-11] have witnessed significant improvements in the outcomes. A technique utilizing a deep-learning approach is proposed in this study to remove JPEG artifacts. In image restoration problems as the compressed and original images are very close, it is efficient to learn the difference between them. Hence the proposed model is based on autoencoders. Autoencoders are feed-forward neural network, in which the output is same as the input. In several image processing applications, including image inpainting[12], deblurring[13], image-to-image translation[14], etc., autoencoders are employed. An encoder, latent space, and decoder are the three components that make up an autoencoder. The input is initially compressed by the encoder into a latent space, and the decoder then reconstructs the original input from this compressed representation. As we go on increasing the depth of the neural network, the accuracy gets saturated at some point and results in an increase in error rate[15]. To overcome this, we used residual learning by adding RRDB blocks in the model. This helps in better learning of our model and also avoids the problem of vanishing gradient. Because of introducing residual learning with autoencoder, the proposed model is named as deep residual autoencoder model.

The proposed model restores the colour image in the YCbCr colour space. The Y-component represents the luminance or brightness of the image, while Cb and Cr are chroma components that represent colour difference information. Among these 3 channels, the Y-channel stores most of the information, which reduces model training time for chroma components(CbCr). Two models are designed to reconstruct both the Y-channel and CbCr channels. The previously proposed models were trained on images that are compressed at specific quality factors only, because of which they were unable to restore images of unknown quality factors. This model is trained on images compressed at a range of quality factors, to make the model generalized.

The outline of this study is: Section II provides an overview of the related literature and the methodology is explained in Section III. Section IV demonstrates the experimental setup for our proposed model. Section V shows comparative results with earlier proposed models. Section VI provides the conclusion for this research study.

II. RELATED WORK

The removal of JPEG artifacts has been the subject of various studies over the past few years, ranging from conventional image processing techniques to the recently emerging field of deep learning-based approaches. There are several studies available that use traditional filter-based approach to reconstruct compressed images. Xiong et al.[4] proposed method which is a simple wavelet-based method for deblocking of JPEG compressed image, which is computationally less complex and still achieves better results compared to previous methods. The method was tested on a standard 512x512 Lena image and compared with the spatially adaptive image recovery algorithm by Yang *et al*.[16]. It is built on the theory of projections onto convex sets, achieving 27 to 32 dB PSNR. The adaptive deblocking filter proposed by Peter List et al.[3], used certain procedures to detect and identify blocking artifacts along edges before attenuating them with a chosen filter. The study proposed by Foi et al. [2] performed very well by suppressing the blocking artifacts to a greater extent, which was based on Shape-Adaptive DCT transform(SA-DCT), but was unable to restore high-frequency information like texture patterns in the original image. The method is tested on both grey-scale and colour Lena image, achieving PSNR values in the range 28 to 36 for grey-scale and 29 to 35 for a colour image.

An alternative approach involves utilizing deep learning techniques, as the filter-based approach for JPEG restoration has certain disadvantages compared to the deep learning approach. The filter-based approach relies on predefined filters, so they are unable to adapt to diverse image characteristics effectively. Also, the filter-based approach leads to limitations such as scalability, generalization issues, and learning capability compared to deep learning-based techniques. Kim *et al*. [9] proposed a single-image super-resolution method, which was inspired by VGG-net. The model is a 20-layer deep neural network, and gradient clipping-based training greatly increases model accuracy. The model is tested on several datasets viz. Set5, Set 14, Urban 100, and B100, achieving PSNR and SSIM of 25 to 37 dB and 0.72 to 0.95respectively. A compact and effective CNN-based artifact removal model called AR-CNN, which was inspired by the SRCNN model[6], was proposed by Dong *et al*. [5]. AR-CNN adds feature improvement layers to the SRCNN's initial architecture. The training of shallow network is performed and for the final 4-layer CNN, it is utilized for initialization. A model utilizing a deep residual autoencoder was proposed by Simone Zini et al.[11]. The model is trained on images compressed at a range of quality factors, 10 to 90 with a step of 10, this makes the model generalized. In previously proposed methods, models are trained exclusively on the Y-channel. This results in chromatic aberration in

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restored images. This model overcomes this drawback by training two different models for the restoration of the Y-channel and CbCr channel respectively. AR-CNN[5], SR-CNN[6], and the model proposed by Simone Zini *et al*.[8] are tested on LIVE1, BSD500, and CLASSIC-5 datasets. For the LIVE1 dataset, these models achieve PSNR and SSIM of 28.98 dB, 28.91 dB, 29.97 dB, and 0.82, 0.81, 0.85 respectively for a quality factor of 10.

Many previous models suffer from some drawbacks. These models are trained on images that are compressed at particular quality factors, resulting in the models being limited to restoring images only at that specific quality factor. But, in a practical sense, information regarding quality factors is unknown to users. For example, images downloaded from the web, from unknown resources, etc. Therefore, in order to make the model generalized, it becomes necessary to train separate models for every distinct quality factor (QF) possible. Our proposed model overcomes this issue by training the model on a diverse dataset comprising images at various quality factors (QFs). The previously proposed methods are only able to restore the luminance component of an image as most of these models are only trained on luma channels of the image without considering its chroma components(Cb and Cr). To address this issue, we propose utilizing two deep residual autoencoder models. The first model focuses on restoring the luma channel and the second one for restoration of chroma components which uses luma channel's result as a guide. The proposed model is inspired by Simone Zini et al.[11] and overcomes some drawbacks associated with it. This model is computationally less expensive than previous one. In the proposed method, the image that has been compressed using JPEG compression algorithm is divided into patches of size 32x32 and transformed to YCbCr colour space and given as input to model. The model takes input of size 32x32 pixels which reduces number of trainable parameters for the model, and results in faster computations and reduces training time.

III. METHODOLOGY

JPEG compression algorithm introduces several artifacts in an image. To overcome this, we provide a technique that uses deep CNN to remove artifacts from the compressed image. The model is trained using denoising autoencoders, with the input being a compressed image and the target being the original, uncompressed version. The dataset has images of 2k resolution, cropped to 1024x1024 size to precisely divide them further into small size patches of 32x32 pixels and given as input. The compressed 32x32 image is converted from RGB to YCbCr colour space. To restore both luma and chroma components, the model architecture consists of two major networks, LumaNet(for Y-channel) and chromaNet(for CbCr channel). LumaNet is an autoencoder that takes the Y-channel as an input and outputs the restored Y-channel. The output of LumaNet is then concatenated with CbCr channels of the compressed image and fed as an input to the ChromaNet. ChromaNet leverages the reconstructed Y-channel as a guide enabling the ChromaNet to recover colour hues and contours in an image. The output of ChromaNet consists of reconstructed Cb, Cr channels. The results of LumaNet and ChromaNet are then concatenated and transformed to RGB format. The proposed method's schematic depiction is shown in Fig. 1.

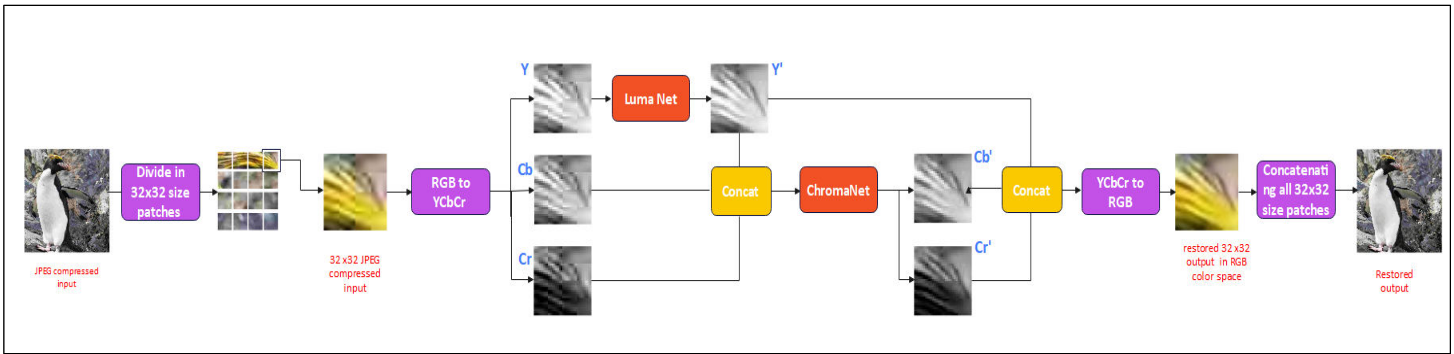

Fig. 1:Visual Representation of proposed method

A. Internal Architecture of LumaNet and ChromaNet

The LumaNet and ChromaNet as depicted in Fig.1, both are denoising autoencoders. As expressed in Fig.2, the JPEG compressed data is taken as an input to encoder. The encoder comprises two 2D convolutional layers, then the output of convolutional layer is passed through the Leaky ReLu activation function. This is further succeeded by an additional convolutional layer and activation function. In the central part, Residual-in-Residual Dense Blocks are connected for feature enhancement and improved learning of the model.

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Table 1: Detailed Description of Architecture: LumaNet and ChromaNet

	Layers	Filter size	Stride	Padding	Output channel
Encoder	Convolution(2d)	3x3	1	1	26
	Convolution(2d)	3x3	1	1	52
	Leaky ReLu				
	Convolution(2d)	3x3	1	1	26
	Leaky ReLu				
RRDB x N					
Decoder	Convolution(2d)	3x3	1	1	52
	Leaky ReLu				
	Convolution(2d)	3x3	1	1	26
	Leaky ReLu				
	Convolution(2d)	3x3	1	1	1
	Tanh				

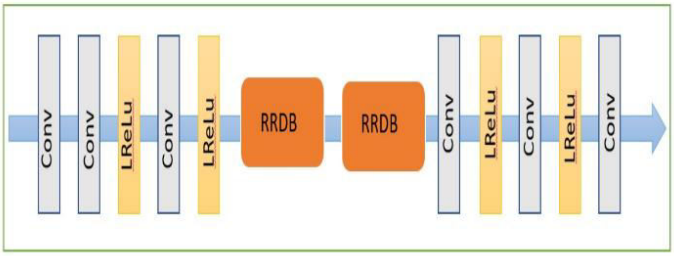

Fig. 2 : Internal Architecture of LumaNet / ChromaNet[11]

(Number of RRDBs, N = 7 for LumaNet, N= 5 for ChromaNet)

RRDB is an extended version of residual blocks that were used in ResNet architecture. The decoder is designed in the same fashion as that of the encoder. There are certain differences in the design of LumaNet and ChromaNet: i) Different numbers of RRDBs are used. For Y-channel restoration, seven RRDB blocks are used in the central part and five for CbCr channels. ii) In ChromaNet, as the input is a concatenation of CbCr channels and restored Y-channel, the encoder incorporates a 3-dimensional convolutional layer. Using the same kernel for Y and CbCr channels facilitates the model in establishing correlations and capturing information regarding the colour and structure of an image. Table 1 depicts the internal structure of LumaNet and ChromaNet.

B. Residual in Residual Dense Blocks (RRDB)

RRDB is a concatenation of one or more residual dense blocks which performs features extraction using densely connected convolutional layers. RRDB is based on the principle of residual learning, which is introduced in a well-known ResNet architecture, and solves the problem of vanishing gradient. Residual Dense Blocks incorporates dense skip connection, by adding an original input to the output of convolution blocks. With an increase in the depth of the neural network, the accuracy initially reaches a saturation point and then deteriorates rapidly [15]. This degradation is not a result of overfitting. Further incorporating additional layers in a deep CNN results in an increase in error rate. To resolve this problem, the ResNet architecture used a skip connection technique that provides an alternate path for the gradient to flow by setting some layers in a deeper network to be identity mapping. This way, the network can propagate gradients and information more effectively throughout the network, facilitating the training of deeper models. Fig.3 depicts internal architecture of RRDB blocks.

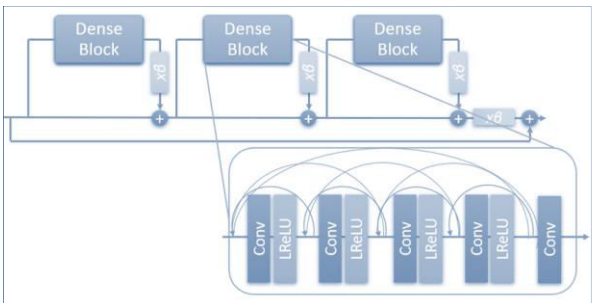

Fig. 3 : RRDB : Internal Architecture[17]

In our proposed method, we have modified the RRDB block and added some skip connections to minimize the error which in turn gives us better results. The number of RRDB blocks for LumaNet and ChromaNet are increased to 7 and 5 respectively.

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IV. EXPERIMENTAL SETUP

A. DATASET USED

The DIV2K [18] dataset is the one that is utilized for training. It has 900 images with a resolution of 2k, of which 800 are utilized to train the model and remaining 100 for testing. Quality factors ranging from 10 to 90 in the step of 10 are used to compress the images. To capture fine details in an image and to lower the model complexity, each image is divided into small size patches of 32x32. Images are then transformed to YCbCr from RGB colour space. After performing all these operations, the dataset consists of 81,92,000 images. From these, 12880 images are selected randomly for training. For comparative study with earlier proposed model, we used LIVE1 dataset [19] for testing.

B. EVALUATION METRICS USED

For assessing the visual fidelity of the restored images in comparison with the original uncompressed images, PSNR and SSIM are employed.

i) Peak Signal to Noise Ratio (PSNR) :

PSNR is a value in decibels, calculated based on the difference in reconstructed image and original uncompressed image. Lower distortion and greater image quality are associated with higher PSNR values.

ii) Structural Similarity Index (SSIM) :

SSIM measures how structurally comparable uncompressed and reconstructed images are. To calculate SSIM, three components are taken into consideration: luminance, contrast, and structure. SSIM is specifically designed to quantify the similarity between two images based on how humans perceive visual information, while PSNR measures pixel-wise differences[20].

Higher values for both metrics indicate greater restored image quality, which means less distortion and restored image is more similar to the original uncompressed image.

C. TRAINING DETAILS

The training of the model is done using python's PyTorch framework (1.8.0) on NVIDIA GTX 1050 GPU with 4GB of memory. The model proposed by Simone Zini *et al.* [11] takes input of size 100x100, was computationally more expensive. To overcome the drawbacks, the model takes the input image of size 32x32 in YCbCr colour space to decrease model complexity and capture fine details. Adam optimizer[21] is used to train the model across 300 epochs with a mini-batch of 16, a learning rate of 0.0002 and parameters $\beta1=0.9$, $\beta2=0.999$. L1 loss is used while training.

V. RESULT AND ANALYSIS

The model proposed in this study is inspired by the deep residual autoencoder-based model introduced by Simone Zini *et al.* [11]., which outperforms the previous studies published based on deep learning such as ARGAN[22], CAS-CNN[23], MWCNN[24], ARCNN[5], and S-Net[25] because of its generalization. We compared our proposed model with AR-CNN and Simone Zini *et.al.* model on the LIVE1 dataset. For comparison, we took results for LIVE1 dataset from their corresponding research paper [5], [11]. Table 2 depicts the comparison between models on LIVE1 dataset based on SSIM and PSNR.

Table 2 : Comparison based on PSNR and SSIM on LIVE1 dataset

Evaluation Metrics	QF	AR-CNN[5]	Simone Zini's model[11]	Proposed model
PSNR	10	28.98	29.97	26.47
	20	31.29	32.34	29.01
	40	33.63	34.78	31.23
SSIM	10	0.821	0.85	0.864
	20	0.887	0.908	0.910
	40	0.93	0.944	0.937

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The proposed model is trained with much lesser computational complexity compared to other models, still achieving comparable PSNR and SSIM values. The study proposed by Wang *et al.*[20] have shown that SSIM correlates better with human visual perception than PSNR. So, in image restoration tasks, SSIM offers more perceptually accurate results. Table 2 depicts that the proposed model is achieving better SSIM results. For better comparative study between models, we compare PSNR and SSIM results in graphical form at quality factor of 10, 20, 40 (Fig.4). Fig.4 shows that for LIVE1 dataset our model is achieving better SSIM values compared to AR-CNN and Simone Zini's model. Fig.5 depicts visual comparison on LIVE1 dataset images for AR-CNN, Simone Zini's model and our proposed model.

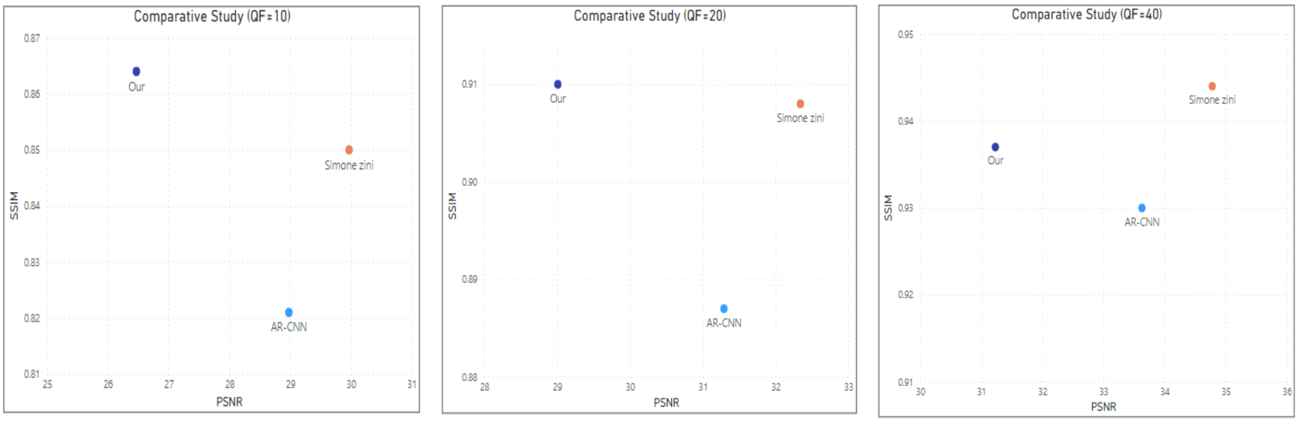
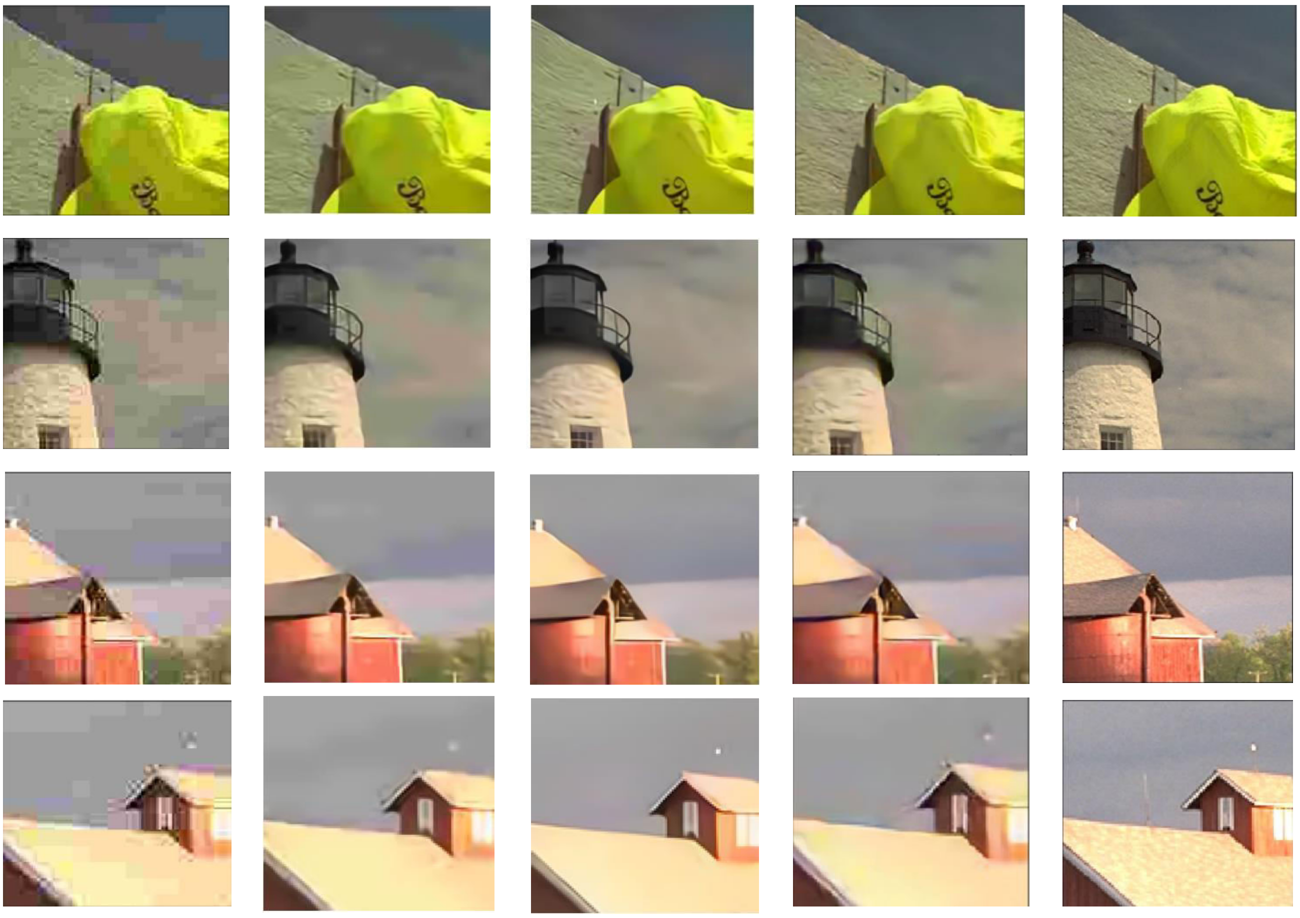


Fig. 4 : Graphical Representation : AR-CNN, Simone Zini's model and proposed model comparison on LIVE1 Dataset at different



Compressed I/P AR-CNN Simone Zini's model OUR Ground Truth

Fig. 5 : Visual Comparison between AR-CNN, Simone Zini's model and our proposed model on LIVE1 dataset

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VI. CONCLUSION AND FUTURE WORK

The proposed model eliminates JPEG artifacts by employing a deep residual autoencoder model. The previous studies based on deep learning for JPEG artifact removal are trained only on images compressed at specific quality factors, which was the most limiting side of those models as they are unable to restore images of unknown quality factors. Our model overcomes this limitation, by training the model on images compressed at different quality factors, which makes the model generalized. The proposed method restores the image in YCbCr colour space with two autoencoders viz. LumaNet and ChromaNet, to restore both luma and chroma components. To overcome the vanishing gradient problem, we make use of residual learning by adding RRDBs in the model. The previous study proposed by Simone Zini et al. which is based on deep residual autoencoder achieved better results, but it is computationally expensive and requires higher training time. In this study, the 32x32 pixel images are used to train the model, that lowers the number of parameters for training, which results in faster computations and reduces training time. In comparison with the previous study, we modified the RRDB architecture and skip connections for both LumaNet and ChromaNet to achieve better accuracy and reduce the error rate. The proposed model is achieving higher SSIM values in comparison with AR-CNN and Simone Zini et al. model on the LIVE1 test. As deep learning is in an evolutionary phase, there is scope for researchers to make advancements in the study proposed for JPEG artifact removal.

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