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Image Inpainting via Generative Multi-column with the aid of Deep Convolutional Neural Networks

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Abstract: **Images can be described as visual representations or likeness of something (person or object) which can be reproduced or captured, e.g. a hand drawing, photographic material. The advent of the digital age has seen the rapid shift image storage technologies, from hard-copies to digitalized units in a less burdensome manner with the application of digital tools. The research aims to design a confidence-driven reconstruction loss while an implicit diversified Markov Random Field (MRF) regularization is adopted to enhance local details. The multi-column network combined with the reconstruction and MRF loss propagates local and global information derived from context to the target inpainting regions. Extensive experiments on challenging street view, face, natural objects and scenes manifest that our proposed method produces visual compelling results even without previously common post-processing. The research involves pre-trained Deep Convolutional Neural Network (DCNN) and their training networks like ResNet50, GoogleNet, AlexNet, VGG-16, resnet18 and densenet201. The average PSNR performance of the ResNet50 model is 25.46db SSIM is 0.929 and MSE is 0.1585, which is superior over comparative techniques.**

Keywords: **Inpainting, Markov Random Field, Deep Convolutional Neural Network, resnet50.**

INTRODUCTION

Image inpainting originated from an ancient technique performed by artists to restore damaged paintings or photographs with small defects such as scratches, cracks, dust and spots to maintain its quality to as close to the original as possible. [1] Image inpainting is an ill-posed inverse problem that has no well-defined unique solution. The evolution of computers in the 20th century, its frequent daily use and the development of digital tools with image manipulation capability, has encouraged users to appreciate image editing, e.g. restoration, and the application of on-screen visual display and special effects to images. As a result image inpainting (henceforth inpainting) has become a state-ofthe-art restoration technique.[2]In a computer vision and graphics context, inpainting is a method that interpolates neighbouring pixels to reconstruct damaged, or defective, portions of an image without any noticeable change on the restored regions when visually compared with the rest of the image.[3]These damaged portions/areas of an image are a set of unconnected pixels surrounded by a set of known adjacent pixels.[4] During the reconstruction of disconnected pixels, the inpainting method uses known-information to fill unknown regions. Image inpainting is an ill-posed inverse problem that has no well-defined unique solution.[5] To solve the problem, it is therefore necessary to introduce image priors. All methods are guided by the assumption that pixels in the known and unknown parts of the image share the same statistical properties or geometrical structures. This assumption translates into different local or global priors, with the goal of having an inpainted image as physically plausible and as visually pleasing as possible [6]. The first category of methods, known as diffusion-based inpainting, introduces smoothness priors via parametric models or partial differential equations (PDEs) to propagate (or diffuse) local structures from the exterior to the interior of the hole [7].Many variants exist using different models (linear, nonlinear, isotropic, or anisotropic) to favor the propagation in particular directions or to take into account the curvature of the structure present in a local neighborhood[8]. These methods are naturally well suited for completing straight lines, curves, and for inpainting small regions.[9] They, in general, avoid having unconnected edges that are perceptually annoying. However, they are not well suited for recovering the texture of large areas, which they tend to blur.[10] The second category of methods is based on the seminal work and exploits image statistical and selfsimilarity priors. The statistics of image textures are assumed to be stationary (in the case of random textures) or homogeneous (in the case of regular patterns).[11] The texture to be synthesized is learned from similar regions in a texture sample or from the known part of the image. Learning is done by sampling, and by copying or stitching together patches (called examplar) taken from the known part of the image, using an exemplar image as a source, and where pixel values are selected one pixel at a time. [12].The proposed method used in the paper to restore the image is ResNet-50. ResNet-50 can easily gain accuracy along with the greatly increased of depth. Since ResNet-50 has a very good performance of image classification, and can extract highquality features of images[13]. Hybrid solutions have then naturally emerged, which combine methods dedicated to structural (geometrical) and textural components.[14] This article surveys the theoretical foundations, the different categories of methods, and illustrates the main applications.[15]

Image recognition can be realized automatically using machine learning, deep learning techniques or other conventional methods [16]. Machine learning is based on the human classification of different types of images, while deep learning extracts features directly from images. In deep learning, the Convolution Neural Networks (CNNs) are used to make predictions. Such networks have recently achieved high accuracy in image recognition applications, in some cases even outperforming humans [17]. On the other hand, thousands of images are needed to gain sufficient accuracy using deep learning techniques. As a consequence, this causes the learning process to be time-consuming, even if Graphics Processing Units (GPUs) are used [18].

LITERATURE REVIEW

He *et al.* (2018) [19] used a dual-phase algorithm (Thieles rational interpolation function and Newton-Theiles function) for adaptive inpainting. This method uses continued fractions to update pixel intensity during the reconstruction of damaged portions based on the surrounding pixel information of known regions along the target region. That is, if the damaged pixel points are vertical, the selected points for interpolation of pixels are in the horizontal direction. The masked image is scanned line by line to locate and adopt information of known pixel points to perform interpolation of pixel intensity.

Ghorai et al. (2018) [20] proposed to use patch selection and refinement method based on joint filtering alongside a modified MRF to enhance optimal patch assignment to perform an inpainting task. This technique uses subspace clustering to select target patches from boundary regions into groups, which are refined via joint patch filtering to capture patterns and remove artefacts.

Wang et al. (2017) [21] used space varying update strategy powered by Fast Fourier transform for full image search. The base technique uses a standard deviation-based patch matching criterion and confidence term that evaluates the spatial distribution of patches to measure the amount of reliable information surrounding the priority point against a known priority point.

Sridevi and Kumar (2019) [22] proposed to use fractional-order derivative (integer-order derivative) with Discrete Fourier Transform (DFT) for inpainting task. The research used this method to achieve a good trade-off between the restored region and edge preservation, and also because DFT are easy to implement. Using fractional order derivative, pixel level on the whole image is considered instead of just considering neighbouring pixel values.

To optimize the network, a conditional constraint loss handles appearance and perceptual features extracted from VGG16 Johnson et al. (2016) [23] using the `1 as base. Both appearance and feature loss use the instance and masked image expressed as a function of the network and the mask. Other losses used are the KL divergence, reconstruction and ongoing adversarial loss. The cross semantic attention layer uses 1×1 convolutions to transform feature maps obtained by instance and masked images to evaluate cross attention before adding them to feed the decoder.

Comparative evaluations were carried out using the baseline models Song et al. (2018), [24] Quantitatively, the performance on 1000 CelebA-HQ images using centre mask of size 128×128 were better than the state-of-the-art. The limitation of this network is that there is a possibility of suffering from mode collapse (i.e. poor diversity in generated images) during training if trained in an unsupervised manner.

PROPOSED METHODOLOGY

Our inpainting system is trainable in an end-to-end fashion, which takes an image X and a binary region mask M (with value 0 for known pixels and 1 otherwise) as input. Unknown regions in image X are filled with zeros. It outputs a complete image$\hat{Y}$. The proposed DCNN based ResNet-50 consists of three sub-networks: a generator to produce results, global and local discriminators for adversarial training, and a pre-trained ResNet-50 to calculate ID-MRF loss. In the testing phase, only the generator network is used.

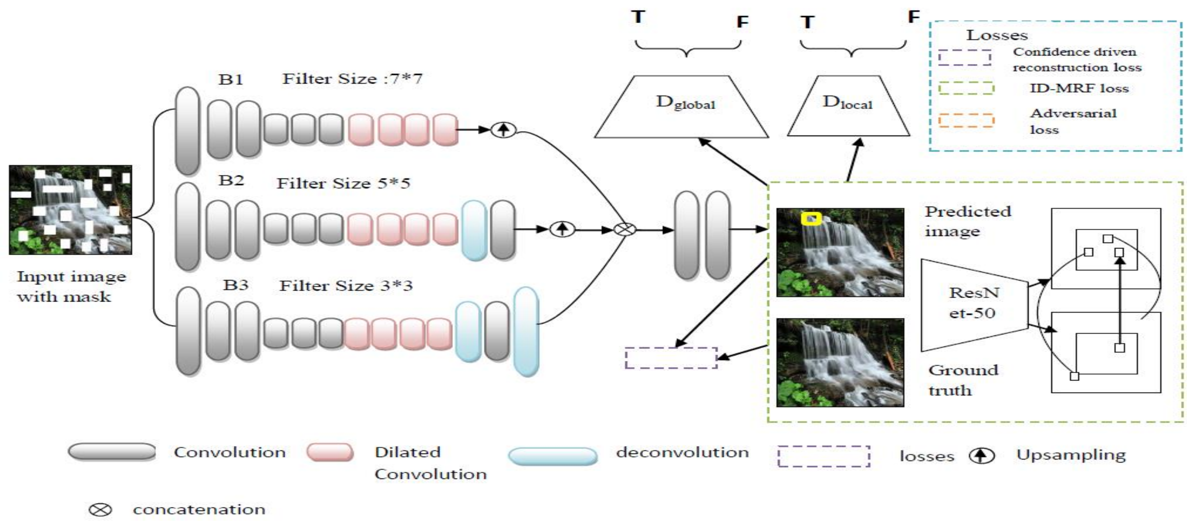


Figure: 1 Proposed Framework with the aid of ResNet-50

ResNet-50

ResNet-50 is short name for Residual Network that supports Residual Learning. The 50 indicates the number of layers that it has. So ResNet50 stands for Residual Network with 50 layers. DCNN have led to number of breakthroughs for image classification. In general the trend is to go deeper number of layers to solve complex tasks and to increase the classification and recognition accuracy. In a general DCNN, many layers are stacked and trained to the task at hand. In residual learning, instead of trying to learn some features, try to learn some residual. Residual can be simply understood as subtraction of feature learned from input of that layer. ResNet does this using shortcut connections (directly connecting input of nth layer to some $(n+x)^{th}$ layer. It has proved that training this form of networks is easier than training simple deep convolutional neural networks and also the problem of degrading accuracy is resolved.

The first problem with increasing depth is gradient explosion/dissipation, which is due to the fact that as the number of layers increases, the gradient back propagating in the network will become unstable with the multiplications and become very large or very small. One of the problems that often arises is gradient dissipation overcome gradient dissipation, many solutions have been found, such as using Batch Normalization, changing activation function to ReLU, and using Xaiver initialization, etc. It can be said that gradient dissipa- tion has been well solved. Another problem with the network deepening is degradation, that is, the performance of the network is worse as the depth increases. From experience, the depth of the network is crucial to the performance of the model. When the number of network layers is increased, the network can carry out more complex feature pattern extraction, so better results can be obtained theoretically when the model is deeper. However, the experiment found that the deep network was degenerating. With the increase of network depth, the accuracy of the network tends to be saturated or even decreased. There is a decrease in the accuracy of the training set. We can determine that this is not caused by overfitting. Because the accuracy of the training set should be high in the case of overfitting. The residual network in ResNet is designed to solve this problem, and after solving this problem, the depth of the network rises by several orders of magnitude.

ResNet proposed two kinds of mapping: one is identity mapping, referring to the "curved curve" in Fig. 2 , and the other residual map- ping refers to the part except the "curved curve", so the final output is $y = F(x) + x$. Identity mapping, as the name implies, refers to itself, which is x in the formula, while residual mapping refers to "difference", that is, $y - x$, so residual refers to F(x). At first, ResNet-50 performed convolution operation on the input, followed by 4 residual blocks, and finally performed full connection operation to achieve classification tasks. The network structure of ResNet-50 is shown in Fig. 2.

Fully connected (FC) layer usually appears at the end of the CNN to summarize the features of the previous layers. If we take the previous convolution and pooling as the process of feature engineering, local amplification and local feature extraction, the latter FC layer can be thought of as feature weighting. The structure of the FC layer shown in Fig. 2 is usually a way to quickly learn the nonlinear combinations of advanced attributes generated by the convolutional layer. The FC layer will learn a possible nonlinear function. The basic procedure of learning is as follows. First, the image, which has been converted into a form suitable for multilevel perceptron, is flattened into column vectors and fed back to the feed forward neural network. The flattened data is then applied to each iteration of the training. In this way, the model has the ability to distinguish between the major features in the image and some low-level features and classify them through classification techniques such as Softmax. Here we will output the classification results of the seven expressions

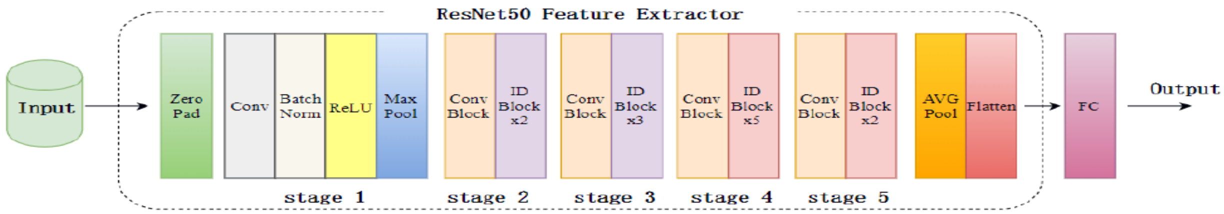
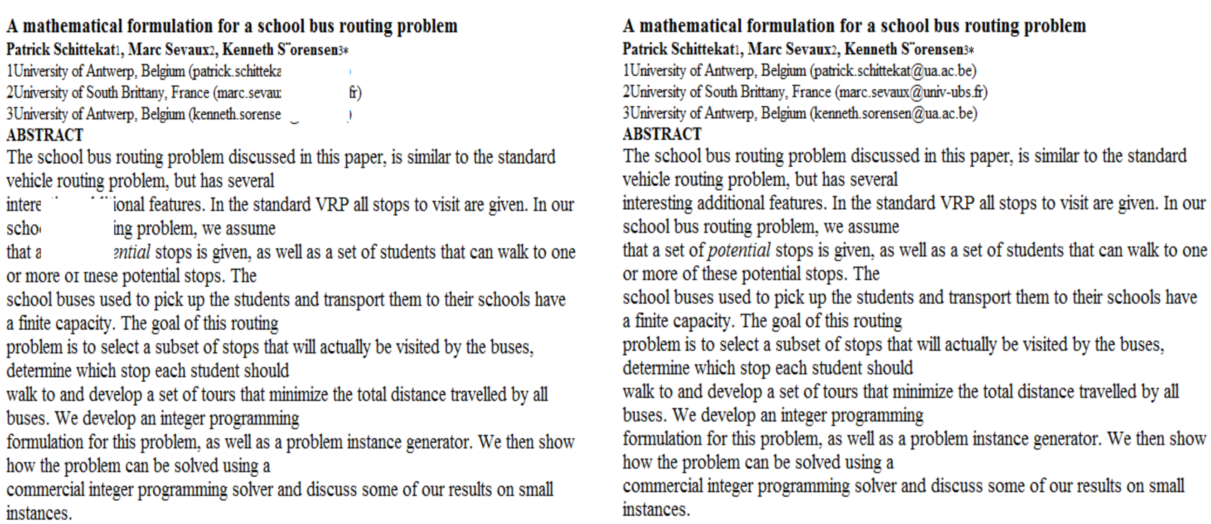


Figure: 2 Block diagram of ResNet-50

RESULTS AND DISCUSSION

The purpose of Image inpainting refers to the process of filling-in missing data in a designated region of the visual input. The research employs Resnet50, Alexnet, vgg16, googlenet, resnet18 and densenet201 for the process of restoring missing pixels in digital images. The research involves six different cases of document images for evaluating the performance of employed techniques. The performance of the employed techniques evaluates through Peak signal-to-noise ratio (PSNR), structural index similarity (SSIM) and Mean Square Error (MSE). It is evident from the investigation that the proposed ResNet-50 attains better performance over comparative techniques. The following figure

The performance of the proposed ResNet-50 attains better values in Peak signal-to-noise ratio (PSNR), structural index similarity (SSIM) and Mean Square Error (MSE) over comparative techniques. The research includes 6 difference cases to evaluate the performance of the proposed approach. It is obvious from the results that proposed ResNet-50 having better performance over other techniques. The figure 3 to 8 shows the visual image comparison for original image and ResNet-50 obtained image with respect to different databases.



A mathematical formulation for a school bus routing problem
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2University of South Brittany, France (marc.sevau fr)
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Figure: 3 Visual comparison of original and ResNet-50 obtained image for case-1

Steps To Loving Yourself- Leads to Respecting Yourself, Leads to Being Respected

STOP ALL CRITICISM- Criticism never changes a thing. Refuse to critcize yourself and others. When you critisize, the only result is negative. Choose to be "Better, not Bitter." Start with how you talk to yourself (weak/whimpee vs. Strong/Healthy/Amazing)

DON'T SCARE YOURSELF- Stop terrorizing yourself with your thoughts (negative whirlpools). Best conversation time- morning. Practice mental wellness. Kill the A.N.T.S.

BE GENTLE, KIND & PATIENT- Treat yourself as someone whom you love. Then treat others this way- creating mutual respect. Talk nicely to yourself and with respect.

CONTROL- :ontrol "YOURSELF."In communication we do NOT have to give an instant knee :sponse. You must practice controlling what you say, how you say it, and then hov empower words or actions from others to affect you.

BE KIND TO YOUR MIND- Gently change your thoughts to more loving thoughts. Our mind, body and health respond to how we talk. Sometimes we have to clearly state OUT LOUD to "stop it". or even smack our wrists, and then say something kind to ourselves.

PRAISE YOURSELF- Criticism breaks down your inner spirit and immune system. Praise builds you up. Humor, joy, quirky. Crown, cloak, skip.

SUPPORT YOURSELF- Reach out to POSITIVE friends/family and allow them to help you. It is being strong to ask for help when you need it most. Allow others to fufill their gifts/purpose. Balance with yourself and your support team.

RELEASING TRIGGERS/PATTERNS-We are creatures of habit and laziness through justification. Take control, this is your one ride. Choose to live optimistically. Be honest with yourself and your past patterns or triggers.

TAKE CONTROL OF YOUR BODY- Learn and APPLY knowled :ion/water. Get enough sleep. Exercise is NOT an option- it is a luxury, privilge a o yourself. You must becuase you can!

MIRROR WORK- "Look" into your eyes, express the growing ser feel for yourself. Wink at your reflection, lighten up. Once a day say "I love you" at yourseır.

PRACTICE DAILY POSITIVES- 2 general I self-specific. TEACH yourself to live optimistically.

RESPECT YOURSELF NOW! Do NOT wait until you make $, or wear a certain size or have... Start practicing today!

Dr. Betty Vanek, 970.686.6006

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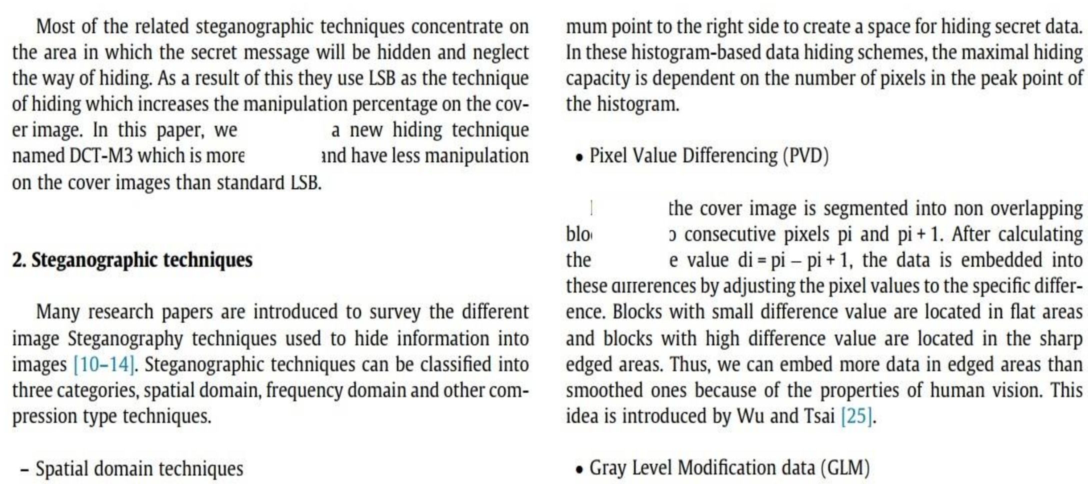
Figure: 4 Visual comparison of original and ResNet-50 obtained image for case-2



Most of the related steganographic techniques concentrate on the area in which the secret message will be hidden and neglect the way of hiding. As a result of this they use LSB as the technique of hiding which increases the manipulation percentage on the cover image. In this paper, we a new hiding technique named DCT-M3 which is more ınd have less manipulation on the cover images than standard LSB.

2. Steganographic techniques

Many research papers are introduced to survey the different image Steganography techniques used to hide information into images [10–14]. Steganographic techniques can be classified into three categories, spatial domain, frequency domain and other compression type techniques.

– Spatial domain techniques

mum point to the right side to create a space for hiding secret data. In these histogram-based data hiding schemes, the maximal hiding capacity is dependent on the number of pixels in the peak point of the histogram.

• Pixel Value Differencing (PVD)

I the cover image is segmented into non overlapping blo ɔ consecutive pixels pi and pi + 1. After calculating the e value di = pi – pi + 1, the data is embedded into these dıfferences by adjusting the pixel values to the specific difference. Blocks with small difference value are located in flat areas and blocks with high difference value are located in the sharp edged areas. Thus, we can embed more data in edged areas than smoothed ones because of the properties of human vision. This idea is introduced by Wu and Tsai [25].

• Gray Level Modification data (GLM)

Figure: 5 Visual comparison of original and ResNet-50 obtained image for case-3

Figure: 6 Visual comparison of original and ResNet-50 obtained image for case-4

- Steganographic in the DWT domain

These techniques work exactly like the techniques that hide data in DCT coefficient but instead of hiding the secret messages into DCT coefficients, the Discrete Wavelet Transform or Discrete Fourier Transform is used as embedding regions as introduced in [33].

- Steganographic in the DFT domain

Naoum et al. [34] presents an enhanced image Steganography system based on discrete wavelet transformation and resilient Back-propagation neural network.

- Steganographic in the Contourlet domain

Sun and Guo [35] introduced a novel image steganography based on contourlet transform and hill cipher. The cover image is decomposed with contourlet transform and one of the subbands is selected to embed the secret data. Then hill cipher is applied to encrypt the secret message.

– Compression-based Hiding Techniques

A lot of non-traditional techniques have been proposed that are not using neither spatial domain of the pixel values nor the frequency domain, instead they use other regions of an image file to embed secret messages.

3. The proposed methodology DCT-M3

As more and more techniques of hiding information (Steganography) are developed, the methods of detecting the use of steganography (Steganalysis), also advance. Most steganography techniques change the properties of the cover source which increases the probability of detecting the changes. The proposed technique introduces a new algorithm for embedding the secret message by trying to minimize the changes in the cover image properties.

To minimize the changes in the cover work we introduced two ideas, the first one is compressing the secret message as long as possible by the current compression techniques, the second idea is using a new hiding technique DCT-M3 which uses the modulus 3 as a base factor for hiding not the traditional LSB technique which uses the modulus 2 as a base factor.

Fig. 2 shows a framework of the proposed DCT-M3 technique. It starts with the compression phase which compresses the secret message in three levels. Then the secret message is embedded into the cover image using DCT-M3 embedding algorithm; during the embedding phase. In the extraction phase, on the receiver side, the DCT-M3 extraction algorithm is used to extract the embedded message.

– Preparing the secret message

The message length is one of the factors affecting the degree of detecting the presence of hidden message. For this reason, we will try to shorten the input message as much as possible to minimize

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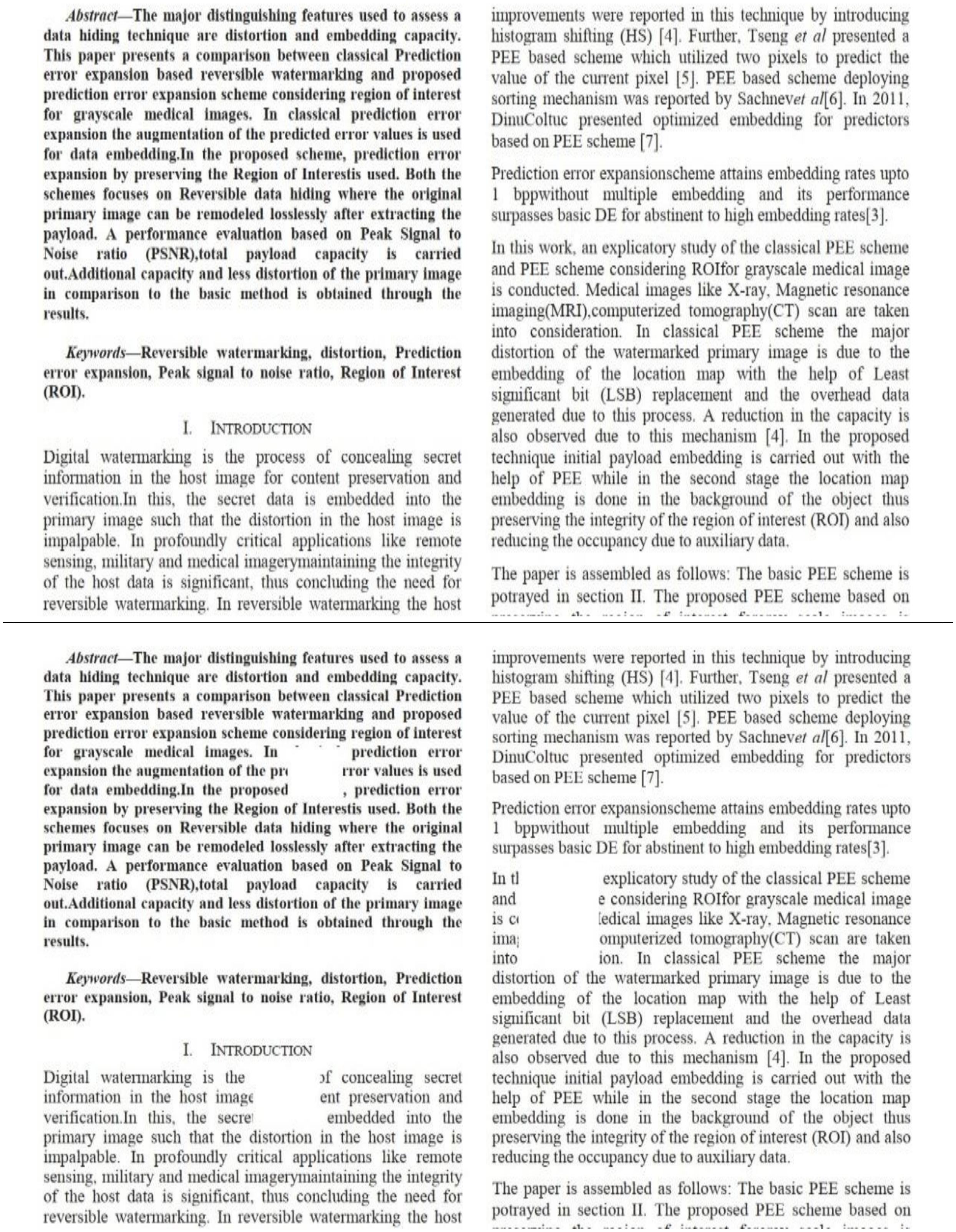

Abstract—**The major distinguishing features used to assess a data hiding technique are distortion and embedding capacity. This paper presents a comparison between classical Prediction error expansion based reversible watermarking and proposed prediction error expansion scheme considering region of interest for grayscale medical images. In classical prediction error expansion the augmentation of the predicted error values is used for data embedding.In the proposed scheme, prediction error expansion by preserving the Region of Interestis used. Both the schemes focuses on Reversible data hiding where the original primary image can be remodeled losslessly after extracting the payload. A performance evaluation based on Peak Signal to Noise ratio (PSNR),total payload capacity is carried out.Additional capacity and less distortion of the primary image in comparison to the basic method is obtained through the results.**

Keywords—**Reversible watermarking, distortion, Prediction error expansion, Peak signal to noise ratio, Region of Interest (ROI).**

I. INTRODUCTION

Digital watermarking is the process of concealing secret information in the host image for content preservation and verification.In this, the secret data is embedded into the primary image such that the distortion in the host image is impalpable. In profoundly critical applications like remote sensing, military and medical imagerymaintaining the integrity of the host data is significant, thus concluding the need for reversible watermarking. In reversible watermarking the host

improvements were reported in this technique by introducing histogram shifting (HS) [4]. Further, Tseng *et al* presented a PEE based scheme which utilized two pixels to predict the value of the current pixel [5]. PEE based scheme deploying sorting mechanism was reported by Sachnev*et al*[6]. In 2011, DinuColtuc presented optimized embedding for predictors based on PEE scheme [7].

Prediction error expansionscheme attains embedding rates upto 1 bppwithout multiple embedding and its performance surpasses basic DE for abstinent to high embedding rates[3].

In this work, an explicatory study of the classical PEE scheme and PEE scheme considering ROIfor grayscale medical image is conducted. Medical images like X-ray, Magnetic resonance imaging(MRI),computerized tomography(CT) scan are taken into consideration. In classical PEE scheme the major distortion of the watermarked primary image is due to the embedding of the location map with the help of Least significant bit (LSB) replacement and the overhead data generated due to this process. A reduction in the capacity is also observed due to this mechanism [4]. In the proposed technique initial payload embedding is carried out with the help of PEE while in the second stage the location map embedding is done in the background of the object thus preserving the integrity of the region of interest (ROI) and also reducing the occupancy due to auxiliary data.

The paper is assembled as follows: The basic PEE scheme is potrayed in section II. The proposed PEE scheme based on

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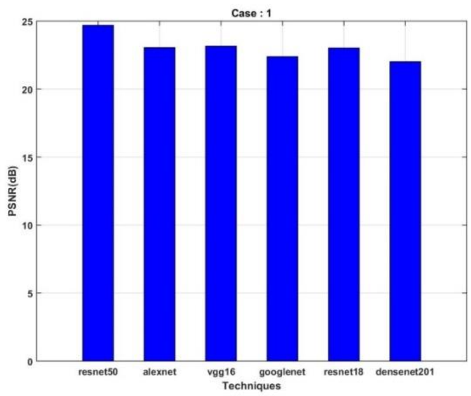
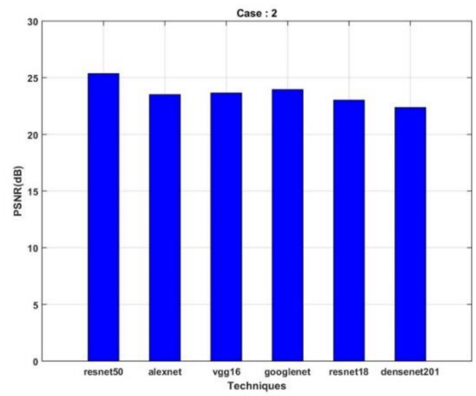
Figure: 7 Visual comparison of original and ResNet-50 obtained image for case-5

Performance evaluation through PSNR

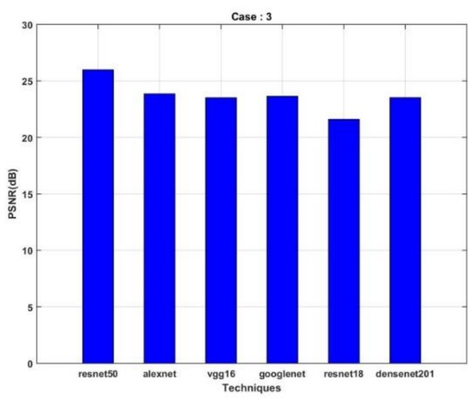
PSNR is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR quantifies the quality of a reconstructed or corrupt image with reference to the ground-truth. The PSNR value approaches infinity as the MSE approaches zero; this shows that a higher PSNR value provides a higher image quality. At the other end of the scale, a small value of the PSNR implies high numerical differences between images. The figure 8 (a) to (f) shows the techniques based PSNR for different employed images. It is evident from all the validation that proposed ResNet-50 having better values over comparative techniques. The average PSNR measure for proposed ResNet-50 achieves 25.46db that is 2.05db better than AlexNet, 2.03db greater than VGG16, 2.14db better than GoogleNet, 3.03db greater than ResNet18 and 3.37db greater than denseNet201. It is evident from all the cases (a) to (f) that ResNet-50 performed superior over comparative techniques.



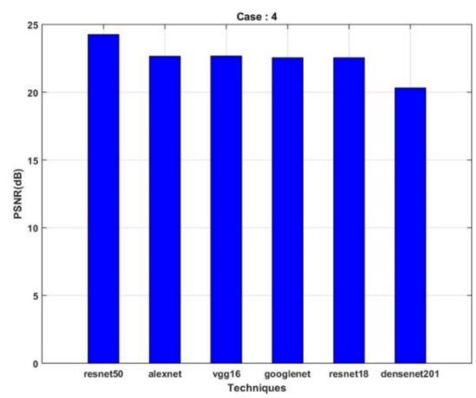
(a)



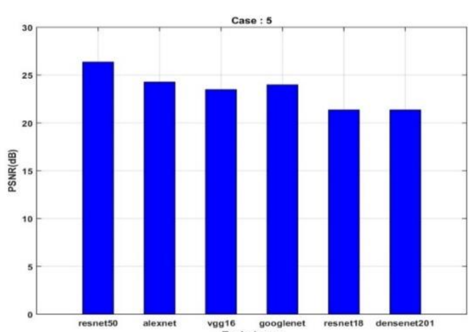
(b)



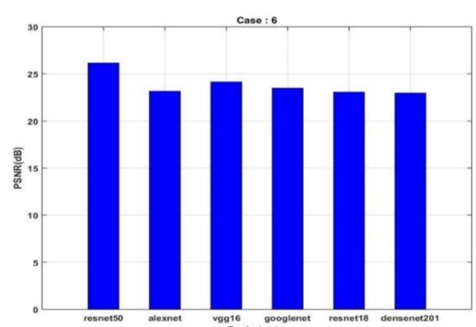
(c)



(d)



(e)

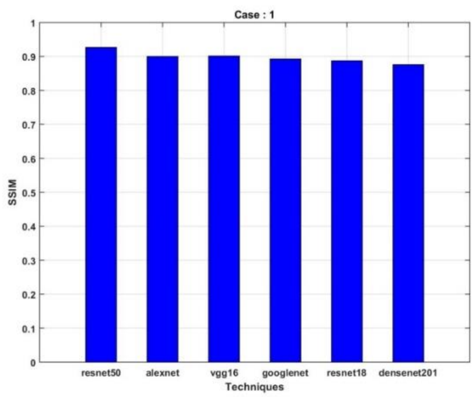


(f)

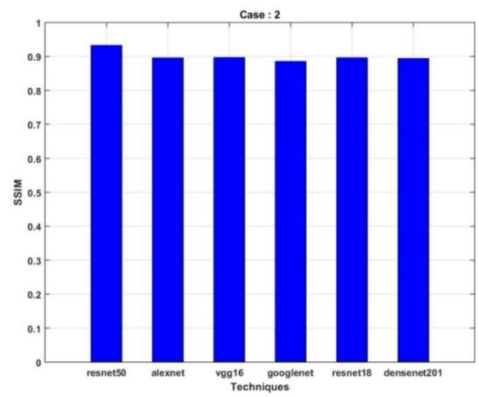
Figure: 8 PSNR comparisons with respect to different techniques

Performance evaluation through SSIM

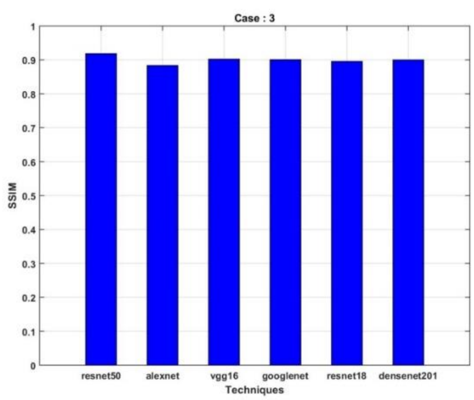
The SSIM is a well-known quality metric used to measure the similarity between two images. It was developed by Wang, and is considered to be correlated with the quality perception of the human visual system (HVS). Instead of using traditional error summation methods, the SSIM is designed by modeling any image distortion as a combination of three factors that are loss of correlation, luminance distortion and contrast distortion. The figure 9 (a) to (f) shows the performance of employed techniques with respect to SSIM. The average SSIM measure for proposed ResNet-50 achieves 0.93 that is 0.029 better than AlexNet, 0.031 greater than VGG16, 0.037 better than GoogleNet, 0.035 greater than ResNet18 and 0.036 greater than denseNet201. It is evident from all the cases (a) to (f) that ResNet-50 performed superior over comparative techniques.



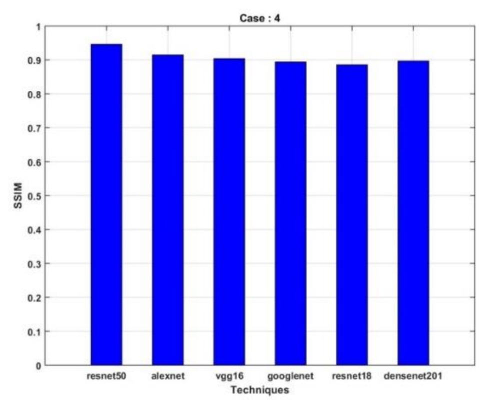
(a)



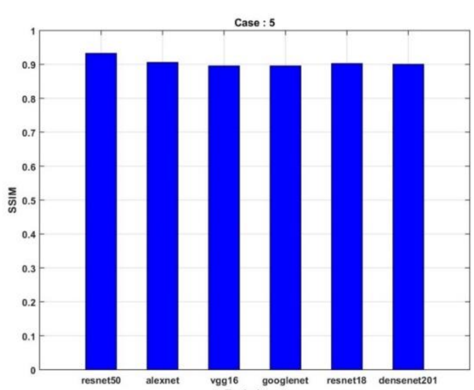
(b)



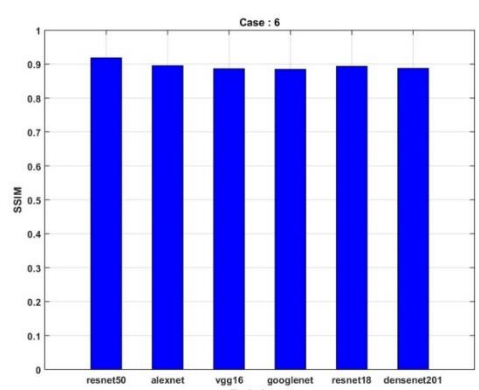
(c)



(d)



(e)



(f)

Figure: 9 SSIM comparisons with respect to different techniques

Performance evaluation through MSE

In the Supervised Learning method, the data set contains dependent or target variables along with independent variables. The building models using independent variables and predict dependent or target variables. If the dependent variable is numeric, regression models are used to predict it. In this case, MSE can be used to evaluate models.

The figure 10 (a) to (f) shows the performance of employed techniques with respect to MSE. The average MSE for proposed ResNet-50 achieves 0.1585 that is 0.1506 lower than AlexNet, 0.1605 smaller than VGG16, 0.2152 lesser than GoogleNet, 0.1668 smaller than ResNet18 and 0.1206 lesser than denseNet201. It is evident from all the cases (a) to (f) that ResNet-50 performed superior over comparative techniques.

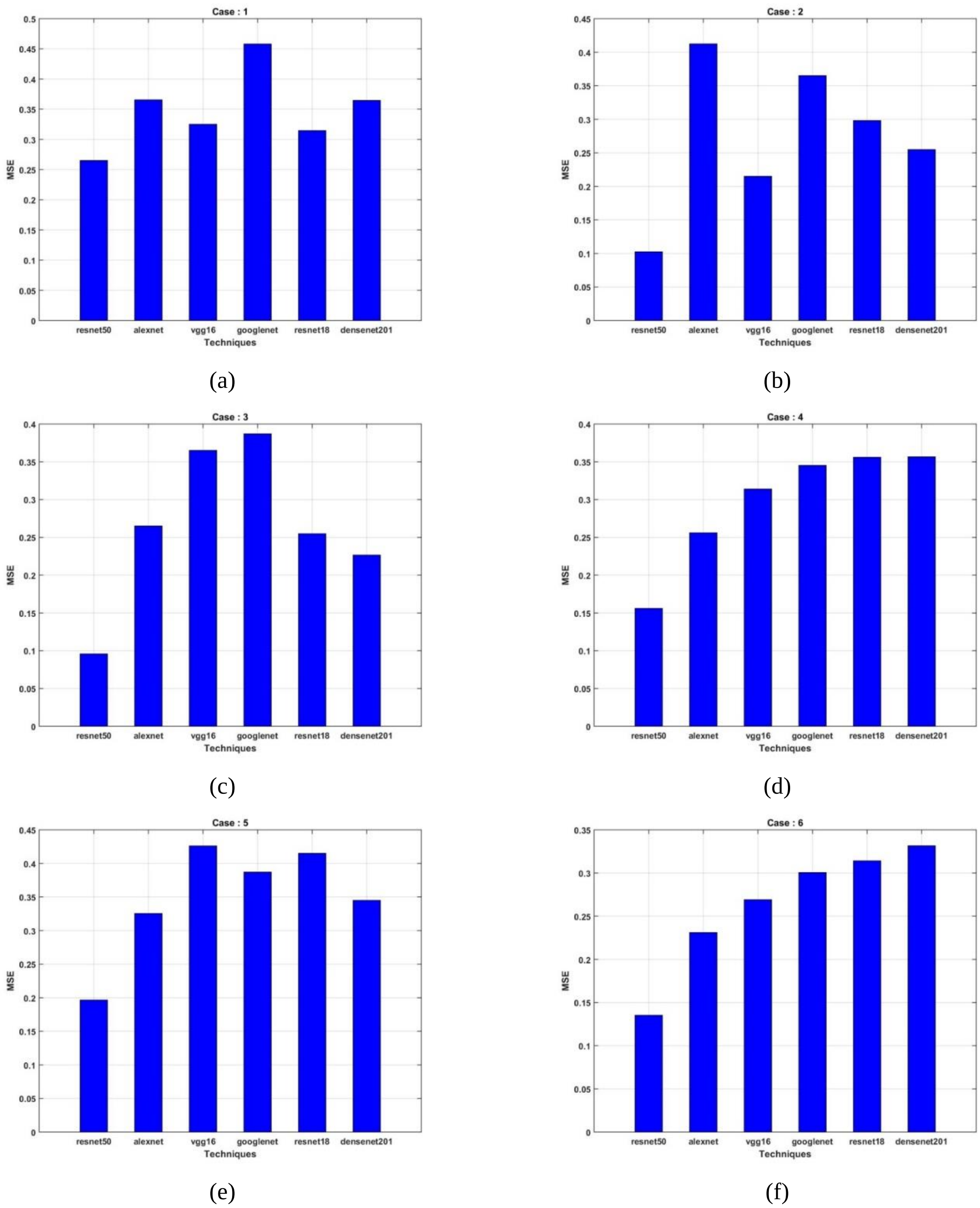


Figure: 10 MSE comparisons with respect to different techniques

CONCLUSION

The quality assessment of inpainted images continues to be a complex and challenging problem. Currently, the research shows growing number of inpainting applications embedded in new generation mobile devices to remove (and reconstruct) certain objects from captured photos. Hence, computational efficiency of inpainting algorithms becomes more relevant to these types of platforms. Image inpainting, from traditional to deep learning methods, has achieved immense, and continued, success. The research investigates different approach for inpainting tasks, datasets, performance evaluation and limitations of the methods. The research identifies the poor performance of traditional methods on images with more extensive binary mask and facial images due to complexity in features on the image. The Research on image inpainting using deep learning has witnessed good progress in recent years. Here, the average performance of proposed ResNet-50 with respect to PSNR is 25.46db that is 2.526db better over comparative techniques, in case of SSIM the ResNet-50 achieves 0.9290, which is 0.0341 greater over comparative techniques and in the case of MSE ResNet-50 achieves 0.1585 error value that is 0.1628 smaller over comparative techniques.

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