

Image restoration using deep learning-based approaches

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Abstract— Techniques for picture restoration try to salvage high-quality images from corrupted or degraded versions. Traditional methods for picture restoration frequently rely on handcrafted elements and presumptions about how an image degrades, which may restrict their ability to handle intricate image distortions. In order to learn intricate mappings from corrupted photos to their corresponding clean versions, deep learning-based algorithms have emerged as a potential approach for image restoration problems. This paper offers a thorough analysis of current developments in deep learning-based picture restoration methods. We go over numerous restoration tasks, such as picture denoising, deblurring, inpainting, and super-resolution, and we highlight the crucial elements and architectures applied in diverse methods. We also provide an overview of benchmark datasets that are freely accessible as well as evaluation measures that are frequently utilised in picture restoration studies. Finally, we explore the field's problems and potential future paths while highlighting possible areas for additional development and study.

Keywords: Image restoration, deep learning , convolutional neural networks ,denoising ,deblurring, inpainting, super-resolution.

1 INTRODUCTION

Old photographs are artefacts that preserve significant people, places, and things. It records crucial events in our lives and brings back memories. We save and treasure these vintage photos because they have meaning and influence for us. Weakening of photographs due to environmental factors such as too much exposure to sunlight, changing of temperature, humidity, handling, and breakdown of chemicals to the photo that was used in the developing process, scratches, missing or damaged areas, water spots, folded photos, and faded colour are just a few examples of problems that require restoration. To produce the best possible results, we proposed a method for restoring the old photos. We presented a strategy for restoring old images in order to achieve the best potential outcomes. This strategy will be simple but effective because it can be used by everyone. Restoration

of ancient images would be easier with the current technology, modernization of the digital age, digital photo upgrades, and restoration processes. We will train two variational autoencoders (VAEs) to translate old and clean pictures into two latent spaces, respectively. Furthermore, to increase the capability of restoring old images from various defects, we must address several degradations intermingled in one old photo, such as structural defects like scratches and dust spots, and unstructured defects like sounds and blurriness. Furthermore, we may use a different face refinement network to restore small details of faces in ancient pictures, resulting in higher-quality photos.

Due to cost and space efficiency, mobiles phones are usually shipped with lower-grade camera lenses and sensors. When taking pictures, especially in the nighttime, the resulting images are usually plagued with dirty pixels, which is the image noise. With the increasing prevalence of mobiles devices, the necessity for an effective noise-removing algorithm is also increased.

Image restoration has been a crucial field of study in computer vision and image processing in recent years. photos can become damaged or corrupted for a variety of reasons, including noise, blurring, inpainting, or low-resolution acquisition. The aim of image restoration techniques is to restore high-quality photos from their corrupted or degraded forms. The handcrafted elements and presumptions about the degradation process that have been used in traditional image restoration techniques. However, these techniques frequently have trouble dealing with complicated image distortions and might not completely capture the essential elements of the restoration operation. Deep learning-based methods have attracted a lot of attention and excelled in a number of computer vision applications to get beyond these constraints. These methods avoid overtly relying on hand-crafted features or established assumptions by making use of deep neural networks to learn complex mappings directly from corrupted images to their corresponding clean versions. Deep learning models can efficiently handle challenging image restoration tasks because they can identify nuanced patterns and correlations in large-scale datasets and generalise well to

unseen data. This paper provides a thorough analysis of current developments in deep learning-based methods for picture restoration. We concentrate on fundamental issues in picture restoration such as image denoising, deblurring, inpainting, and super-resolution. We go over the reasons for using deep learning techniques for these tasks and highlight their benefits over more conventional approaches. Overall, the goal of this study is to present a thorough overview of deep learning-based picture restoration techniques, covering a range of restoration tasks, architectures, evaluation measures, and future possibilities. We aim to stimulate additional study and development in this interesting sector by highlighting the recent developments and exploring the difficulties ahead.

2 LITERATURE SURVEY

In their publication, Ran Li, Lin Luo, and Yu Zhang offered a solution to the image restoration problem. 'Half-Quadratic Splitting using Convolutional Neural Network'

'Image Restoration Method'. It employs two approaches: model-based optimisation and discriminative learning. The researchers' main goal was to incorporate a trained convolutional neural network (CNN) for denoising as a model into a model-based optimisation strategy for solving picture restoration challenges. However, they utilised a Gaussian denoising model, which is insufficient to restore the details of low-quality photos in all circumstances.

'Poisson noisy image restoration via overlapping group sparse and nonconvex second-order total variation priors' is another image restoration paper. They employed the TVOGS and MM algorithms, the Alternating direction method of multipliers [ADMM], and the Iteratively reweighted least squares algorithm [IRLS] in their paper, which was written by Kyongson Jon, Jun Liu, Xiaoguang Lv, and Wensheng Zhu. It is more difficult to optimise than Gaussian deblurring because to the ill-conditioned non-quadratic data fidelity term. Ganzhao Yuan and Bernard Ghanem offered a technique to image restoration in their paper [1] 'l0TV: A New Method for Image Restoration in the Presence of Impulse Noise' published in *ieeexplore*, with their main goal picture restoration in the presence of impulse noise.

Impulse sounds are most common in data capture and are caused by malfunctioning sensors or analogue to digital converter faults. Total Variation (TV) [l0TV-PADMM], MPEC (Mathematical Programme with Equilibrium Constraints), and proximal Alternating Direction Method of Multipliers (PADMM) were among the approaches employed. Uwe Schmidt and Stefan Roth's

major goal in [4] 'Shrinkage Fields for Effective Image Restoration' was to design an effective approach to image restoration that combines both computational efficiency and great restoration quality. They used the Kodak dataset to train and test their model. They employed techniques such as Half-Quadratic Optimisation, Shrinkage Function, and Cascading of Shrinkage Fields. However, a more efficient GPU implementation could be developed to substantially optimise runtime for huge image sizes. [5] 'Noise2Noise: Learning Image Restoration without Clean Data' by Jaakko Lehtinen, Jacob Munkberg, Jon Hasselgren, Samuli Laine, Tero Karras, Miika Aittala, and Timo Aila used Convolutional neural network (CNN) to restore images on BSD300 and IXI-T1 datasets. As in low-light photography, the L1 loss recovers the median of the targets, i.e. the expectation of the distorted input data.

3 METHODOLOGY

A. PIL(Python Image Library) The Python Pillow module is based on PIL (Python Image Library). It is one of the most important Python modules for image processing. However, Python 3 does not support it. However, we may use this module as a PIL with Python 3.x. It can handle a variety of image formats, including jpeg, png, bmp, gif, ppm, and tiff. Using the pillow module, we can do anything with the digital photographs. We'll learn how to filter photographs, create thumbnails, merge images, crop images, blur an image, resize an image, create a water mark, and many more actions in the next section. The image is displayed using the image class from the Python pillow library. The pillow package's image modules include a few built-in functions, such as loading images and creating new ones.

B. PyTorch PyTorch is a tensor library designed for use in Deep Learning applications with GPUs and CPUs. It is an open-source machine learning package written in Python that was primarily developed by the Facebook AI Research team. Along with TensorFlow and Keras, it is one of the most popular machine learning libraries. NumPy is a well-known open-source Python toolkit for scientific and mathematical computations. It also allows you to work with massive multi-dimensional arrays and do calculations using linear algebra, Fourier transforms, and matrices. Pandas, Matplotlib, and OpenCV are just a few of the many supporting libraries for NumPy. PyTorch is well-known for its popularity in research rather than production. PyTorch, on the other hand, has seen rapid growth in professional developer adoption since its release a year after TensorFlow. Because of PyTorch's tight integration, you get: • Better memory and enhancement • More sensible error messages • Finer-

grained control of model structure • More transparent model behaviour • Improved compatibility with NumPy

4 THE PROPOSED SYSTEM

The proposed system consists of the following stages

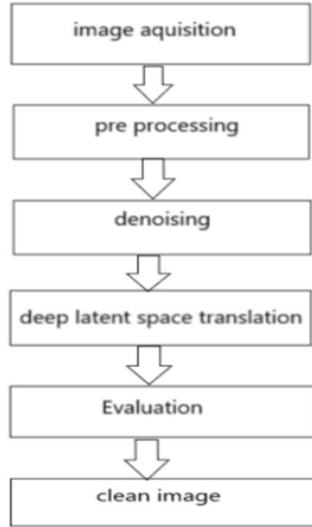


Figure 1: depicts the flowchart of our model.

In this part, the image restoration model is explained. Images can be damaged in many ways. This deterioration can be occurred in various forms like noise, blur, scratches, missing few parts etc., Different images have different level of degradation. Hence restoring damaged images is a challenging task. A. Image acquisition In this section the system gets the input image. B. Pre-processing The first step performed on the image is pre-processing. In this stage, the image is processed using standard techniques. C. Denoising The goal of noise reduction is to reduce noise in natural photographs while preserving original features and increasing signal-to-noise ratio (SNR). D. Deep latent space translation In this we train two variational autoencoders (VAEs) to transform old photos and clean photos into two latent spaces.

The framework is trained on two VAEs(variational autoencoders): VAE1 is trained for pictures in real photos r R and synthetic images x X, while VAE2 is trained for clean images y Y. Images are converted to compact latent space using VAEs. The mapping then uses a partial non-local block to restore the corrupted (blurry, noisy, damaged) images to clean ones in the latent space. The primary goal of this initiative is to bridge the gap between data and authentic historic photographs. To translate and clean old photographs into two latent spaces, we train two variational autoencoders (VAEs). Synthetic paired data is used to learn the translation between these latent areas. As a result, the learned network can generalise effectively to real-world images.

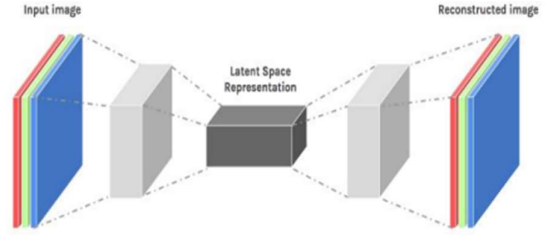


Figure 2: depiction of neural network

Figure 2: depiction of neural network

In Figure 2, we can notice that initially the input image (png format) is converted into grey scale image. Then, it is sent to encoder which compresses the image using loss less compression so that all the extraneous information (such as noise, blur, etc.) and focuses only on the important pixels. This is then sent to decoder which will enlarge the image to its original size while storing the important pixels. At the end, we will be getting the reconstructed image without any degradations.

5 RESULTS

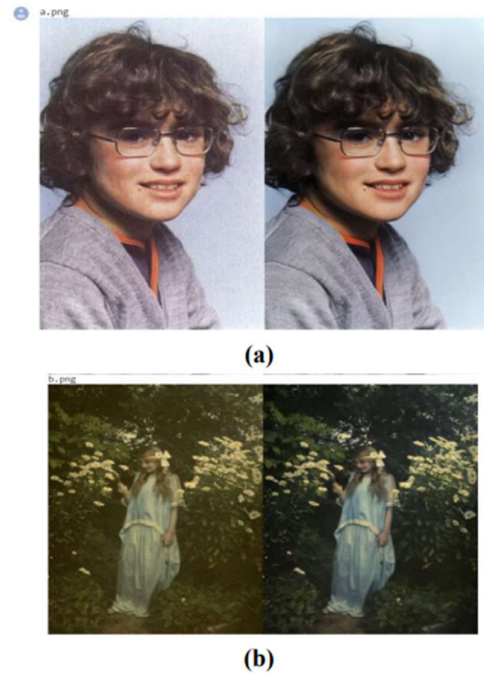


Figure 4: The images (a), (b) shows the outputs by restoring the degraded image.

Output for scratch detections:



(c)



(d)

Figure 5: The images (c), (d) shows the outputs in which the scratches which are due to degradation are removed.

6 APPLICATION OF IMAGE RESTORATION

1. Image restoration has played a critical role in the field of imaging in astronomical applications defined by poisson and Gaussian noise.
2. Medical imaging, such as computerised tomography (CT) and magnetic resonance imaging, benefit from the SR approach (MRI) Multiple photos can be acquired because the resolution is limited while the resolution quality is not. This can aid the surgeon in performing more precise operations on the particular portion of the body.
3. Multispectral image restoration can be performed on satellite imagery's multispectral bands in order to improve the resolution of the collected satellite images.
4. To improve the mobile camera's HR.
5. Motion blur estimation can be conducted in real-time video image processing systems in order to improve video resolution.

7 CONCLUSION

Image restoration is a difficult topic to solve. The primary goal of this project is to do a comparative analysis. Though each strategy has its own way of dealing with the situation and its own set of benefits and drawbacks. The use of the methodologies is governed by the comprehension, requirement, and standard of the output required, as shown by the previous explanations. The descriptor that results is compact, discriminative, and efficient. We have shown clear data that have drawn a reduction in complexity and an increase in the capacity to learn very complex aspects since the introduction of this method. This method, we hope, will be effective for future jobs involving the extraction of strong discriminative characteristics.

8 REFERENCES

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3. Shrinkage Fields for Effective Image Restoration: https://openaccess.thecvf.com/content_cvpr_2014/papers/Schmidt_Shrinkage_Fields_for_2014_CVPR_paper.pdf .
4. Image restoration segmentation using watershed method for basic medical applications: <https://ph02.tcithaijo.org/index.php/past/article/view/244125/165992>
5. IMAGE RESTORATION FUNDAMENTALS AND ADVANCES BY Bahadir k Gunturk and Xin Lee
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9. TV: A New Method for Image Restoration in the Presence of Impulse Noise <https://ieeexplore.ieee.org/document/7299175> .
10. Poisson noisy image restoration via overlapping group sparse and nonconvex second- order total variation priors <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0250260> .

REVIEW

1. In the article you gave, the shortcomings of current machine learning methods for picture restoration are discussed, and a brand-new on-demand learning algorithm is suggested as a solution. The authors specifically contend that current models might overfit to particular levels of image corruption and fall short of generalising to more difficult levels of corruption. They suggest an approach to get around this restriction by generating training cases where they are most needed, enabling the model to become more adaptable to different levels of corruption. The authors use four picture restoration tasks and three datasets to demonstrate the efficacy of their methodology, which outperforms both the standard training technique and alternative curriculum learning methods. The article's overall message emphasises the significance of overcoming the shortcomings of present machine learning methods for picture restoration and outlines a promising new approach to increase these models' generalizability.

2. The paper you gave is a review of recent research on picture restoration techniques that can improve first responders' (FRs') situational awareness during rescue operations in inclement weather. The article specifically focuses on the deraining, desnowing, and dehazing families of image restoration techniques. The authors review the research on these techniques, paying particular attention to how deep learning models are used and how well they fit the criteria for use in rescue operations. The article's main point is the possibility of picture restoration techniques based on deep learning models to improve first responders' situational awareness during rescue missions in inclement weather. The authors give a thorough overview of the techniques and their applicability for this application by reviewing recent literature and presenting a faceted taxonomy. Researchers developing picture restoration techniques to aid first responders in rescue operations may find this survey to be helpful.

3. With a focus on deep learning-based methods, the authors offer insightful information about the state-of-the-art in picture restoration techniques for first responders. The authors offer a helpful tool for academics working on picture restoration techniques for this particular application by reviewing the literature and developing a faceted taxonomy. The paper also emphasises how these techniques may enhance first responders' situational awareness during rescue missions in inclement weather.

4. In this article, the significance of repairing ancient photographs—many of which have undergone various

forms of degradation—is discussed, and a deep neural network-based technique is suggested. The background and significance of the topic are introduced, and then general convolutional neural networks and generative adversarial networks are discussed along with their principles and structures. The article describes the design and loss function of the suggested picture restoration technique, which is based on these networks. The research concludes with experimental findings that demonstrate the suggested algorithm performs better than previous algorithms in blur repair and damage repair, making it more appropriate for the restoration of ancient pictures. The post does note that there is still space for improvement in terms of fixing broken photos, and that is where future work will be concentrated.

5. The paper addresses conventional approaches for image restoration and how deep learning's debut has greatly enhanced image restoration efficiency. Using widely used quantitative evaluation indices, many deep learning-based restoration algorithms are compared and examined. The quality of picture restoration can be improved by using an appropriate loss function during the network creation and training process, according to the report.

6. Indeed, picture restoration using deep learning approaches has produced encouraging results, particularly when dealing with intricate and severely damaged images. Large-scale data collection and autonomous learning techniques can be used to get around common image restoration problems and enhance the quality of recovered photos. As you pointed out, further research is still required to determine how well these strategies work when dealing with various kinds of image degradations and combinations of degradations.

7. It is true that as technology has advanced, computers have gotten better and better at doing things that were previously only possible for people to do. One such task that computers are effective at performing is image restoration. Image restoration techniques provide a solution to the issue of how to preserve ancient and damaged photographs, which cannot be overstated. However, it can be difficult to repair photographs that have been damaged by numerous kinds of noise and flaws.

8. It's exciting to see that your suggested method for restoring degraded images—using a pre-trained convolutional neural network—can minimise noise and blur without the use of laborious iterative methods. The fact that your technology has produced good deblurring outcomes is also encouraging. It's crucial to remember that additional study is required to see whether it works for other kinds of image degradations or combinations of degradations. More thorough results and comparisons

with other cutting-edge approaches in the field would be beneficial.

9. In the paper, a deep learning architecture for Poisson picture denoising is proposed. This design performs better than conventional techniques, especially when the noise level is high. Low-light and photon-limited environments frequently experience poisson noise, which the suggested design can accurately handle. Convolutional and deconvolutional layers are combined with symmetric connections in the architecture. In tests using the image peak values 4, 2, and 1, the network outperformed benchmark traditional techniques by a statistically significant margin in terms of PSNR increases. By adjusting the reconstruction stride sizes, the denoising network can run more quickly. Despite being somewhat shallow in comparison to contemporary designs, the suggested network can execute Poisson denoising without being explicitly taught the noise properties and can learn the parameters from data alone. Future study can look into how well this architecture handles different types of noise, such Gaussian noise or random noise with unknown properties, as well as other imaging issues like deblurring or inpainting.

10. This paper describes a cutting-edge machine learning method for signal reconstruction. Without explicit image priors or likelihood models of the corruption, the authors show that it is possible to train a model to restore images by solely using corrupted instances. In some cases, the trained model's performance may even be better than models that were trained using uncontaminated data. The authors demonstrate how this method may be applied to a variety of tasks, such as the removal of photographic noise, the denoising of artificial Monte Carlo pictures, and the reconstruction of undersampled MRI scans, all of which are affected by various processes. The findings imply that this method has the potential to be a potent tool for a variety

CONCLUSION:

We went through several fascinating and essential research papers published Image restoration utilising deep learning-based approaches and even other methods in the following assignment and provided reviews for the following.

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REVIEW

1. The paper “Image Super-Resolution Using Deep Convolutional Networks” presents a significant contribution to the field of image super-resolution. By the introduction of the SRCNN architecture, the authors demonstrate the effectiveness of deep learning techniques in solving the problem of enhancing the resolution of low-resolution images. One strength of the paper lies in the proposed network architecture, which is designed to capture and leverage the hierarchical features in image through convolution layers. The authors also provide a clear description of the training strategy, which involves pre-training and fine-tuning steps. This approach enables the network to learn the

mapping between low-resolution and high-resolution patches effectively.

It is worth noting that the paper was published in 2014 when deep learning for image super-resolution was still in its early stages.

Overall, the paper provides a solid foundation for deep learning-based image super-resolution and serves as a starting point for further research in the area.

2.The paper "Deep Image Prior" introduces a fascinating concept that leverages the structure of deep neural networks for image restoration tasks. The deep image prior demonstrates that the randomly-initialized weights of a network can capture meaningful prior knowledge about natural images, allowing for effective restoration without explicit training.

However, it's important to note that the deep image prior is not a panacea for all image restoration challenges. The method has limitations, such as its sensitivity to initialization and the need for careful hyperparameter tuning. Moreover, the restoration quality heavily depends on the specific architecture and network initialization. the paper "Deep Image Prior" presents an innovative idea that exploits the structure of deep neural networks as a prior for image restoration. It offers a promising direction for further exploration and inspires future research in the field of deep learning-based image restoration.

3.The paper "Deep Exemplar-Based Colorization" presents an interesting approach to colorizing grayscale images using deep learning and exemplar-based learning. The idea of leveraging color exemplars to guide the colorization process is a significant contribution, as it provides a way to transfer realistic and coherent colors to grayscale images. The utilization of a deep CNN architecture allows the model to learn the complex mapping between grayscale and color images. . The network learns to capture the local image context and predict appropriate color values. This deep learning approach enables the method to generalize well to various grayscale inputs.

the paper "Deep Exemplar-Based Colorization" introduces a compelling approach to colorizing grayscale images using deep learning and exemplar-based learning The combination of deep CNNs, patch matching, and propagation techniques allows for the transfer of realistic and coherent colors The results demonstrate the potential of the method in producing visually pleasing colorizations.

4.The paper "Deep Image Demosaicking Using a Cascade of Convolutional Neural Networks" presents a significant contribution to the field of image demosaicking .The proposed cascaded CNN architecture leverages the spatial and spectral correlations in the

image to improve the quality of demosaicked images. One of the strengths of the paper lies in the cascaded architecture, which enables progressive refinement of the demosaicked image. By incorporating multiple stages, the network can iteratively learn and refine the spatial and spectral details, leading to enhanced demosaicking performance. It's worth noting that the paper mainly focuses on demosaicking using a Bayer pattern, which is a common pattern used in many image sensors However, different sensors may employ different patterns, and the generalizability of the proposed method to other patterns is not explicitly discussed. the paper "Deep Image Demosaicking Using a Cascade of Convolutional Neural Networks" presents a compelling approach for image demosaicking The cascaded CNN architecture and the integration of spatial and spectral information contribute to improved demosaicking performance The results demonstrate the effectiveness of the proposed method, showcasing its potential for practical demosaicking applications.

5.The paper "Fast and Accurate Image Super-Resolution with Deep Laplacian Pyramid Networks" presents a significant contribution to the field of image super-resolution. The proposed approach combines the Laplacian pyramid framework with deep CNNs to achieve real-time performance while generating high-quality super-resolved images. One of the strengths of the paper lies in the design of the network architecture .The Laplacian pyramid networks provide a multi-scale representation of the images, allowing for the capture of details at different scales. The CNNs then learn to enhance these details, resulting in high-quality super-resolved images. It's worth noting that the paper was published in 2017, and since then, there have been further advancements and variations in network architectures and training strategies for image super-resolution It would be beneficial to consider more recent papers and techniques to explore the latest developments in the field. the paper "Fast and Accurate Image Super-Resolution with Deep Laplacian Pyramid Networks" presents an effective and efficient approach for image super-resolution.

6.The paper addresses the challenge of reconstructing MR images accurately and efficiently from under-sampled data while considering data privacy regulations and the difficulty of collecting and sharing large amounts of data The authors propose a solution based on federated learning, which allows for collaborative training using MR data from different institutions while preserving patient privacy.

Federated Learning (FL): The use of FL enables collaboration and model training across multiple institutions without sharing sensitive patient data This approach addresses data privacy concerns while

leveraging the MR data available at different institutions. **Cross-Site Modeling:** To overcome the issue of domain shift resulting from variations in data collection protocols, sensors, disease types, and acquisition protocols across institutions, the authors propose a cross-site modeling approach. This technique aligns the learned intermediate latent features across different source sites with the distribution of latent features at the target site. **Experimental Evaluation:** The paper presents extensive experiments on four datasets with diverse characteristics to evaluate the proposed FL-based framework. The results demonstrate the potential benefits of the approach, including improved generalization and the advantages of multi-institutional collaborations.

the paper proposes a FL-based framework for MR image reconstruction that leverages multi-institutional data while preserving patient privacy. The cross-site modeling approach addresses domain shift issues, and the experimental results demonstrate the potential benefits of the proposed method. However, a detailed review of the research paper would require access to the full paper and experimental findings.

7. The paper emphasizes the recent use of deep learning techniques for image reconstruction in medical imaging, acknowledging the impressive performance of deep learning models in various vision applications. It presents a review of deep learning image reconstruction approaches and provides an overview of widely used databases in this field.

the article identifies the key challenges facing deep learning in medical image processing, such as the need for large amounts of data and the issue of domain shift. It discusses possible directions to overcome these challenges and highlights the promising future of deep learning in medical image reconstruction. The presented literature aims to leverage the advantages of deep learning in medical imaging, ultimately enhancing the capabilities of artificial algorithms to assist radiologists in their diagnostic tasks. the overview provides a general idea of the topics covered in the article, it does not provide specific details or insights from the reviewed literature. To gain a deeper understanding and comprehensive review, it would be necessary to access the complete article.

8. The study used twenty digital brain phantoms and simulated 15-minute full-ring PET scans using the Monte Carlo simulation toolkit, SimSET. Partial-ring PET data were generated by removing coincidence events that hit specific detector blocks. A convolutional neural network (CNN) based on the residual U-Net architecture was trained to predict full-ring data from the partial-ring data, either in the projection or image domain. The study used twenty digital brain phantoms and simulated 15-minute full-ring PET scans using the

Monte Carlo simulation toolkit, SimSET. Partial-ring PET data were generated by removing coincidence events that hit specific detector blocks. A convolutional neural network (CNN) based on the residual U-Net architecture was trained to predict full-ring data from the partial-ring data, either in the projection or image domain. Based on the simulation results, the study suggests that DL has the potential to recover partial-ring PET images and improve image quality in cases where incomplete projection data are obtained.

9. The review begins with a brief introduction to conventional image processing techniques used in PET. It then explores the integration of deep learning into PET image reconstruction, discussing approaches that utilize deep learning-based regularization or establish a fully data-driven mapping from measured signals to images. The focus is on how deep learning can enhance the accuracy and quality of reconstructed PET images. The review also covers deep learning-based post-processing methods for various aspects of PET imaging, including low-dose imaging, temporal resolution enhancement, and spatial resolution enhancement. These techniques leverage deep learning algorithms to improve image quality, reduce noise, and enhance details in PET images.

Finally, the review addresses the challenges associated with applying deep learning to enhance PET images in a clinical setting. It discusses factors such as data availability, generalizability, interpretability, and regulatory considerations. Furthermore, it outlines future research directions aimed at overcoming these challenges and advancing the field of deep learning in PET image .

the review provides an overview of the current state of deep learning methods in PET image processing, highlighting their potential benefits and discussing avenues for future development and application in clinical practice.

10. By using a neural network, this approach offers a new framework for conducting holographic imaging, addressing spatial artifacts such as twin-images and self-interference. The neural network is trained to rapidly and accurately reconstruct phase and amplitude images of objects using a single hologram, reducing the need for additional measurements and significantly improving computational efficiency. To validate the method, the researchers reconstructed phase and amplitude images of various samples, including blood and Pap smears, as well as tissue sections. The results demonstrate the effectiveness of using machine learning techniques in overcoming challenging problems in imaging science. This approach opens up new possibilities for designing powerful computational imaging systems. the study showcases the potential of employing deep learning and neural networks for phase recovery and holographic

image reconstruction The method offers a faster and more efficient approach to holographic imaging while producing high-quality results.

Reference:-

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- 8.Partial-ring PET image restoration using a deep learning based method
- 9.Deep learning-based image reconstruction and post-processing methods in positron emission tomography for low-dose imaging and resolution enhancement
- 10.Phase recovery and holographic image reconstruction using deep learning in neural networks