**Image inpainting using deep generative models**

**Review 1)**

Inpainting in natural photos has been effectively accomplished using generative adversarial networks. However, the medical imaging industry has not yet embraced the most recent cutting-edge models to a great extent. As the chest exam is the most popular radiological procedure, we examine in this study how well three newly published deep learning-based inpainting models—context encoders, semantic picture inpainting, and the contextual attention model—perform when applied to chest x-rays. We learn to forecast the centre 64 64 region in each patch using 1.2M 128 128 patches from 60K healthy x-rays as the training data for our generative models. On both the normal and pathological radiographs, we test the models. By comparing the PSNR ratings and visually inspecting the data, we assess the outcomes.

**Review 2)**

DTI is currently a promising method for in vivo research on WM microstructure. Nevertheless, it includes challenges that must be taken into account at each particular analytical stage, starting with the planning of the experiment and ending with the interpretation of the findings. This page has outlined the typical issues encountered when doing DTI studies and some potential solutions, providing helpful advice and references, including the most popular tools for each stage of the typical DTI pipeline. We think that the description of the most popular products and tools in the DTI workflow has thus far been undervalued. As a result, we think that our hitchhicker's guide will not only be useful for newbies to the field

**Review 3)**

In this article, molecular diffusion and its use in diffusion MRI are explained. Diffusion MRI makes use of the random movements of molecules known as molecular diffusion to examine the structure of neural tissue. It explores how interactions with tissue components cause water diffusion in the brain to deviate from free diffusion. Diffusion MRI can map white matter fibre pathways and has clinical uses in brain ischemia. The potential of diffusion tensor imaging (DTI) for analysing diffusion anisotropy and its application to the research of brain development and psychiatric illnesses are mentioned in the article. Additionally, it covers diffusion MRI artefacts and offers references for more information.

**Review 4)**

For multimodal integration, surface-based intersubject analysis, longitudinal analysis, and pre-surgical planning, accurate and reliable alignment of brain images is essential. Registration accuracy typically needs to be better than 1 mm due to the size of the implicated brain regions. Instead of matching intensities between two images or by matching tissue boundaries, our novel alignment method, Boundary-Based Registration, or BBR, adjusts alignment by maximising image contrast across tissue boundaries.

**Review 5)**

Although the practise of "image inpainting," or fixing outdated or damaged photos, has been around for a while, it has recently become more well-known because to advances in image processing technology. Automatic picture inpainting has found significant applications in computer vision and developed into a significant and difficult area of research in image processing as a result of the advancement of image processing tools and the flexibility of digital image editing. This study examines the existing image inpainting techniques, which were divided into sequential-based, CNN-based, and GAN-based approaches. A list of techniques for various types of visual distortion is also provided for each category. The paper also includes public datasets in its presentation.

**Review 6)**

Traditional inpainting techniques typically use vast picture databases or textures that are most similar to the areas around the missing region. Recently, data with low rank have demonstrated that non-convex optimisation reduces measurements. In this study, we present a new picture prior that assumes prior knowledge of image gradients at a low rank. The low rank regularisation to gradient similarity minimization used by the proposed detail-preserving image inpainting algorithm is known as gradient-based low rank approximation (Grad-LR), in which we apply low rank constraints to the image's horizontal and vertical gradients before reconstructing the desired image using adaptive iterative singular-value thresholding of both derivatives.

**Review 7)**

In this research, we provide a low-rank Hankel structured matrix completion method for patch-based image inpainting. The suggested technique takes advantage of the shift-invariant filter and image data annihilation property that is seen in many of the inpainting methods currently in use. In particular, the picture inpainting problem is transformed into a low-rank structured matrix completion problem by taking advantage of the commutative property of the convolution, which causes the annihilation property to produce a low-rank block Hankel structure data matrix. To adjust to local changes in the image statistics, the block Hankel structured matrices are created patch by patch. We use an alternate direction approach of multipliers with factorization matrix initialization and the low-rank matrix fitting algorithm to solve the structured low-rank matrix completeness problem.

**Review 8)**

In this article, we discuss a brand-new, efficient, and useful approach for geometric object surface change. A surface can be continuously changed into a different shape by using a space-mapping approach on a specified or damaged area. The suggested method is applied to mesh smoothing and surface retouching issues. The method actually relies on a local processing of polygonal data that can be used to fair 3D meshes. We approach the issue from a single point of view, namely that of the space-mapping technique based on the construction of radial-basis functions, and regard shape transformation as a general sort of operation for surface modification. The effectiveness of our mesh-modeling tool is demonstrated by the inclusion of experimental results.

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**Review 10)**

Convolutional networks are effective visual models that produce feature hierarchies. We demonstrate that semantic segmentation using convolutional networks alone, trained end-to-end, pixels-to-pixels, outperforms the prior best practise. Our fundamental discovery is the ability to construct "fully convolutional" networks that can learn and infer effectively from inputs of any size while producing outputs of any size. We describe fully convolutional networks in detail, explain how they might be used to spatially dense prediction applications, and make linkages to earlier models. In order to transfer their learnt representations to the segmentation challenge, we convert current classification networks (AlexNet, the VGG net, and GoogLeNet) into fully convolutional networks.

**Reference**

1) Link: <https://arxiv.org/abs/1809.01471>

2) Link; <https://www.frontiersin.org/articles/10.3389/fnins.2013.00031/full>

3) Link] <https://onlinelibrary.wiley.com/doi/10.1002/jmri.20683>

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