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A Comparison of Deep Learning and Conventional Image Processing For Contrast Enhancement and Automatic Segmentation of Super-Resolution Neural Brain Images

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ABSTRACT

The segmentation and analysis of neuronal and fibril structures collected by electron microscopy in order to create 3D maps of brain connections is a time-consuming scientific project. In computer vision and neuroscience, this is a domain. Interactive comprehension of neuronal and fibril connections in the brain Neuroscientists can take substantial conclusions from the brain. Conclusions for artificial intelligence applications, improved comprehend the condition and maybe discover a treatment Biomedical imaging technologies that are currently in use Enhancement and segmentation frequently fail to generalize find non-convex shapes and deep relationships the mind. Deep learning is contrasted with machine learning in this study to comprehend classical mathematical image processing its potential as a viable contrast solution super-resolved image enhancement with auto-segmentation Images of neuronal brains.

Key Words: Deep Learning, Image Processing, Contrast Enhancement, Auto-Segmentation, Deep-Tissue Super Resolution, Neuronal Network.

INTRODUCTION

Image interpretation and processing are sensitive to the image's complexity, wide variances among interpreters, computational cost, data availability, application-specific needs, and memory. Manual analysis of neuronal data is prone to human mistake and is typically time-consuming and difficult due to enormous advancements in the availability of data and picture capture technologies. Another option is to use machine learning[1] to automate the activities of contrast enhancement and auto segmentation. Traditional machine learning approaches such as regression, clustering, and classification, on the other hand, are unable to deal with the complexities of recognising and segmenting neuronal fibre structure in a super-resolution picture of the brain. Deep learning models are extremely beneficial in extracting complex information and features from input images with promising accuracy, and they have been identified as a potential method for key implementation of image processing and segmentation tasks such as neuronal fibre identification in brain images[2]. Deep learning methodological advancements have had a significant impact on medical image processing, image interpretation, image fusion, image segmentation, computer-aided diagnosis, and image-guided therapy[3].

The goal of this study is to present a thorough analysis, comparison, and problems of a deep learning-based strategy for contrast enhancement and auto-segmentation of super-resolved neuronal brain pictures when compared to classic mathematical image processing approaches.

NON DEEP LEARNING IMAGE ENHANCEMENT TECHNIQUES

It is critical to examine possible non-deep learning-based techniques[4] that may be employed for contrast enhancement in order to develop a potential comparative research between deep learning and non-deep learning-based approaches. As explained in the next section, intensity transformations such as log transformation and gamma transformation, as well as picture quality enhancers such as histogram equalisation used for contrast augmentation, often entail direct modification of image pixels.

- Log Transformation: Maps the greater range of high-intensity input levels x to a narrow range of output levels y, whereas the narrow range of low-intensity values x is mapped to a broader range of output values y, i.e. it compresses the dynamic range of pictures with considerable pixel value fluctuation.Log Transformation is represented mathematically by $y = \log(1+b*x)$, where b is a constant.

- Gamma Transformation: Fractional r values (0.2-0.6) translate a limited range of dark input values x to a larger range of output values y, allowing for general-purpose contrast modification. Gamma Transformation is represented mathematically by $y = c * (xr)$, where c is a constant.

- Histogram Equalization: When the image's useful data is represented by near contrast values, this approach typically raises the global contrast. This guarantees that the image's intensity range has been efficiently spread out equally, allowing areas of lower contrast to achieve a greater contrast, resulting in noise removal[5]. Pixel-wise picture processing for contrast enhancement may result in an unexpected fluctuation in the intensity of background pixels, resulting in the addition of sudden noise to the image. Applications such as identifying deep fibril structure in a brain MRI frequently need a high level of precision and accuracy. As a result, a more generic contrast enhancement approach with higher accuracy and computational efficacy is required.

AUTO SEGMENTATION TECHNIQUES WITHOUT DEEP LEARNING

To comprehend the benefits of deep learning-based autosegmentation[6] for identifying fibril structure across different layers in a brain image, a comparison study with other existing segmentation algorithms such as edge detection, thresholding, clustering, and the marker-controlled watershed algorithm[7] is required. Picture segmentation techniques (edge detection, thresholding, clustering, and watershed) fundamentally separate a digital image into subsets of linked pixels and assign a unique label to each pixel, i.e. pixel-wise image segmentation. A more thorough examination finds that edge detection produces preferred results in photos with finer border characteristics, such as a flower, thresholding produces preferable results in images with less features, such as a cricket ball, and clustering produces preferable results in segmenting images. segmenting photos that may be equally categorised into two or more subclasses, for example, spotting a blockage in a cardiac blood artery Applications such as tumour detection in brain MRI scans may be seen as a classification challenge, and as a result, these algorithms frequently perform well. In general, image segmentation problems that do not require sub-pixel accuracy of classification or connecting pixels, i.e., problems with more well-defined divisions, are likely to be satisfactorily solved using algorithmic image segmentation implementations, such as separation of bones from tissues, separation of lungs from ribs, and so on.

However, when it comes to identifying fine neuronal structure in a brain MRI, the algorithmic implementation will be ineffective.

As a result, resilience in implementation is necessary for identifying distinct fibril-structures in pictures with subpixel accuracy[8].

WHY DEEP LEARNING OVER TRADITIONAL IMAGE ENHANCEMENT TECHNIQUES

Sharpening, noise reduction, and contrast improvement are all part of image enhancement. Human perception frequently influences an acceptable image enhancing process, resulting in disparity and discrepancy. Furthermore, conventional mathematical image processing Methods for contrast enhancement operate effectively only in a fixed situation at the expense of deterioration in other picture properties, resulting in unanticipated negative consequences such as over enhancement and halo effect. Image enhancing methods such as histogram equalisation and cumulative histogram equalisation are very indiscriminate, increasing the contrast of background noise while diminishing the useful signal. Supervised CNNs[9] provide feature tracking between a training low resolution and high resolution picture pair, guaranteeing that contrast enhancement does not degrade other image properties such as image sharpness and noise content.

Furthermore, unlike pixel-wise traditional image enhancement techniques that may fail to achieve contrast enhancement for super-resolved neuronal images due to the involvement of sub-pixel accuracy, CNNs[10] can be trained to meet application requirements by adding more details to the training set, i.e. feeding the deep learning model with more high-resolution images. The availability of memory devices, training data, transfer learning, and high-speed processors has further altered deep learning's preference over previous picture enhancing techniques[11].

WHY AUTO SEGMENTATION WITH DEEP LEARNING OVER MANUAL SEGMENTATION

Image segmentation is the categorization of pixels in an image into separate groups with comparable characteristics. Image segmentation may be divided into three categories: manual, semi-automatic, and autosegmentation. Recent advancements in technological modalities and time constraints for manipulating large amounts of data, particularly in the field of biomedical imaging, have established auto-segmentation as a far superior, faster, and more convenient alternative to manual and semi-automatic segmentation methods[12]. Manual segmentation procedures, such as regional growth from seeds, are extremely biassed and discriminative, resulting in segmented output heterogeneity.

Deep learning-based auto-segmentation[2] can be a faster, more repeatable, and more reliable solution than manual segmentation assuming enough training data is available to learn the model's predicted parameters. The usefulness of manual, semi-automatic, or auto-segmentation is greatly reliant on the application's complexity, computing effectiveness, and the availability of annotated segmented data.

OPEN RESEARCH CHALLENGES

1. Scalable data availability: Supervised learning in deep convolutional neural networks for image processing applications such as super-resolution and autosegmentation necessitates data for training, cross-validation, and testing of the proposed model. Due to the inclusion of sub-pixel precision, obtaining scalable annotated data for mapping from input variables to output variables in a deep convolutional neural network is difficult for contrast enhancement and autosegmentation of neuronal fibres.
2. Deep learning-based auto-segmentation lacks generalisation capabilities, which is a significant disadvantage compared to contrast enhancement. In other words, deep learning models are biassed by their particular training datasets, leaving little room for transfer learning[13], whereas contrast augmentation allows for generalisation. This demonstrates the need of having appropriate manually segmented training data for auto-segmentation.
3. Memory and Computational Cost: Deep learning and artificial intelligence systems rely on large amounts of data to train theorised parameters. Memory requirements for storage and algorithm computational effectiveness are two critical elements for real-world biomedical imaging applications, which are an active research topic in the semiconductor design industry.
4. Overfitting: To assure good results on the testing dataset, it is critical to prevent overfitting or large variance in the proposed model. Overfitting in a deep learning model can cause major errors in pixelwise super-resolution and auto-segmentation of neural structures if the training and testing datasets are vastly different.

5. Image Quality Assessment: Choosing an appropriate image quality assessment[14] is critical for establishing a quantitative and robust foundation for comparing results obtained after deep learning processing with available ground truth data, as it affects the model's consistency, completeness, and predictive capability. The decision between reference and reference-less picture quality measures is influenced by computational complexity and agreement with human perception of image quality[15].

CONCLUSION

This comparative study sheds insight on the use of Deep Learning (DL) algorithms for contrast enhancement and auto-segmentation to discover neural connections across many brain levels. Non-DL based picture quality enhancement approaches such as Log and Gamma Transformations and Histogram Equalization are examined and compared to DL based contrast enhancement utilising CNNs to determine the superiority of deep learning over traditional mathematical image processing methods.

To generate a comparative viewpoint, non-DL based auto-segmentation methods such as edge detection, thresholding, clustering, and watershed algorithms are studied. Deep learning is a complex study area in image processing and computer vision.

Deep learning technologies will be used in future works and research to facilitate the main implementation of a certain application at low cost and computational effectiveness. This research investigates deep learning as a viable solution for visual analysis of neuronal structure in the brain of a drosophila.

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