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Deep Learning Approximation of Perceptual Metrics for Efficient Image Quality Evaluation Using AI Based Hybrid Method

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Abstract

Through the continued development of technology, applying deep learning to remote sensing scene classification tasks is quite mature. The keys to effective deep learning model training are model architecture, training strategies, and image quality. From previous studies of the author using explainable artificial intelligence (XAI), image cases that have been incorrectly classified can be improved when the model has adequate capacity to correct the classification after manual image quality correction; however, the manual image quality correction process takes a significant amount of time. Therefore, this research integrates technologies such as noise reduction, sharpening, partial color area equalization, and color channel adjustment to evaluate a set of automated strategies for enhancing image quality. These methods can enhance details, light and shadow, color, and other image features, which are beneficial for extracting image features from the deep learning model to further improve the classification efficiency. In this study, we demonstrate that the proposed image quality enhancement strategy and deep learning techniques can effectively improve the scene classification performance of remote sensing images and outperform previous state-of-the-art approaches.

Keywords: image quality; remote sensing; scene classification; deep learning; explanation artificial intelligence.

I. Introduction

With the progress of science and technology and the further popularization of computer, human beings are no longer satisfied with sensing and processing external information only by their own organs. The subject of artificial intelligence has drawn wide attentions from industry, academia and media. It uses machines to simulate the human mind to deal with a large number of physical information, so as to achieve a certain subjective image recognition, natural language recognition and other image thinking work. The extensiveness of artificial intelligence makes the related application research reach deeply into many fields and achieved remarkable results, among which image recognition is one of the most representative technologies. The ability of human eyes on image resolving is outstanding. To achieve an image recognition system to replace human eyes and brain has been a goal pursued by human beings for many years. Image recognition utilizes computers to simulate the process how human beings analyse and understand target images. Research shows that 60% of human perception information comes from the sense of vision, so the research of image recognition is of great significance [1]. In the recent 20 years of development, the objects of image recognition have gradually enriched from simple words, numbers to human faces, scenes and fine targets, etc. With the emergence of new technologies such as machine learning, excellent methods such as artificial neural networks and support vector machine classification have also injected new vitality into the image recognition technology. At present, the technology has shown great application value in numerous fields such as criminal investigation, biomedicine, astronomy and meteorology, financial banking, multimedia network communication, food testing, industry, agriculture and so on, and has extensive research prospects.

Ii. Research Motivation

Computer-aided diagnosis (CAD) has emerged as one of the most important research fields in medical imaging. In CAD, machine learning algorithms are often utilized to examine the imaging data from historical samples of patients and construct a model to assess the patient's condition [1]. The developed model assists clinicians in making quick decisions. The most common imaging modalities used in medical applications are X-ray, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and ultrasound. The sole aim of medical image processing would be to improve the interpretability of the information illustrated [2]. The following are the main categories of medical image analysis: enhancement, registration, segmentation, classification, localization, and detection [3].

Earlier, medical images were processed using low-level methods, such as thresholding, region growing, and edge tracing [4]. Meanwhile, the growth in size and scope of medical imaging data has fueled the evolution of machine learning techniques in medical image analysis. However, since such methods rely on handcrafted features, algorithm design requires manual effort. These constraints of conventional machine learning approaches have risen to the notion of artificial neural networks (ANNs). Factors such as data availability and computational processing capabilities facilitate the deepening of ANNs [5]. The emergence of deep learning techniques like convolutional neural networks has widened the possibilities for the automation of medical image processing.

A convolutional neural network (CNN) is a class of neural networks meant to handle pixel values. CNN makes image classification more scalable by employing linear mathematical concepts to detect patterns inside an image. While traditional CNN architectures consisted solely of convolutional layers placed on top of one another, modern architectures such as Inception, ResNet, and DenseNet come up with new and innovative approaches to building convolutional layers in a way that makes learning more efficient [6].

CNN can be employed as a feature extractor as well. Feature extraction aims to convert raw pixel data into numerical features that can be processed while keeping the information in the original data set. Traditional feature extractors can be replaced with CNNs, which can extract complex features that express the image in much more detail. The resulting features are then fed into a classifier network or used by typical machine learning algorithms for classification [7].

Despite the fact that deep CNN architectures exhibit cutting-edge performance on computer vision problems, there are some concerns about using CNN in the radiology field. In 2014, Good fellow et al. discovered that introducing a little bit of noise to the original information can readily deceive neural networks into misclassifying items [8]. Furthermore, since the efficiency of deep learning is often based on the volume of input data, CNN requires large-scale, well-annotated radiology images. Building such databases in the medical industry, on the other hand, is costly and labor-intensive.

Iii. Medical Image Analysis Using Deep Learning

The primary focus of medical image analysis is to find out which regions of the anatomy are affected by the disease to aid physicians in learning about lesion progression. The analysis of a medical image is mostly reliant on four steps: (1) image preprocessing, (2) segmentation, (3) feature extraction, and (4) pattern identification or classification [4]. Preprocessing is used to remove unwanted distortions from images or improve image information for further processing. Segmentation refers to the process of isolating regions, such as tumors, and organs, for further study. The process of extracting precise details from the regions of interest (ROIs) that aid in their recognition is known as feature extraction. Based on extracted features, classification assists in categorizing the ROI.

We have compiled a list of research papers primarily concerned with segmentation and classification in medical imaging. Following the review of CNN, we have outlined some techniques for improving CNN's performance.

Iv. Image Quality Assessment

Due to the widespread use of image super-resolution techniques, evaluating the quality of reconstructed images has become increasingly important. Image quality refers to the visual properties of an image, and the methods of image quality evaluation, distinguished from the point of view of human involvement, include two branches: subjective and objective evaluation. Using subjective evaluation, we can determine the quality of an image (whether it appears realistic or natural) based on statistical analysis and with a human being as the observer. This type of method can truly reflect human perception. The objective evaluation of an organization is usually conducted based on numerical calculations utilizing some mathematical algorithm that can automatically calculate the results. In general, the former is a straightforward approach and more relevant to practical needs, but these methods are difficult to implement and inefficient.

Mean squared error (MSE)

The average of the squared differences between predicted and actual values. It penalizes larger errors more heavily.

Accuracy

The ratio of correctly predicted instances to the total number of instances. It's commonly used for balanced datasets but can be misleading for imbalanced datasets.

V. Image Enhancement

Image enhancement refers to the process of manipulating an image to improve its visual quality and interpretability for human perception. This technique involves various adjustments that aim to reveal hidden details, enhance contrast, and sharpen edges, ultimately resulting in an image that is clearer and more suitable for analysis or presentation. The goal of image enhancement is to make the features within an image more prominent and recognizable, often by adjusting brightness, contrast, color balance, and other visual attributes.

Standard image enhancement methods encompass a range of techniques, including histogram matching to adjust the pixel intensity distribution, contrast-limited adaptive histogram equalization (CLAHE) to enhance local contrast, and filters like the Wiener filter and median filter to reduce noise. Linear contrast adjustment and unsharp mask filtering are also commonly employed to boost image clarity and sharpness.

In recent years, deep learning methods have emerged as a powerful approach for image enhancement. These techniques leverage large datasets and complex neural network architectures to learn patterns and features within images, enabling them to restore and enhance images with impressive results.

Vi. Deep Learning

Deep learning is a subset of machine learning that uses multi-layered neural networks, called deep neural networks, to simulate the complex decision-making power of the human brain. Some form of deep learning powers most of the artificial intelligence (AI) in our lives today.

By strict definition, a deep neural network, or DNN, is a neural network with three or more layers. In practice, most DNNs have many more layers. DNNs are trained on large amounts of data to identify and classify phenomena, recognize patterns and relationships, evaluate posssibilities, and make predictions and decisions. While a single-layer neural network can make useful, approximate predictions and decisions, the additional layers in a deep neural network help refine and optimize those outcomes for greater accuracy.

Deep learning drives many applications and services that improve automation, performing analytical and physical tasks without human intervention. It lies behind everyday products and services—e.g., digital assistants, voice-enabled TV remotes, credit card fraud detection—as well as still emerging technologies such as self-driving cars and generative AI.

Vii. Proposed Methodology

A neural network is a computational model inspired by the structure and functioning of the human brain. It consists of interconnected nodes, or artificial neurons, organized in layers. Information flows through these layers, with each neuron receiving input, processing it using activation functions, and passing the output to the next layer. Neural networks are commonly used for various tasks in machine learning and artificial intelligence, such as pattern recognition, classification, regression, and more complex tasks like natural language processing and image recognition.

Here are the fundamental steps involved in the functioning of a neural network:

Input Layer: The neural network receives input data, which could be anything from numerical values to images or text. Each input is represented by a neuron in the input layer.

Weighted Sum: Each input neuron is connected to neurons in the next layer via connections called synapses. These connections have associated weights that determine the strength of the connection. The neural network calculates the weighted sum of inputs and weights for each neuron in the next layer.

Activation Function: After calculating the weighted sum, an activation function is applied to introduce non-linearity into the network. This activation function determines whether a neuron should "fire" (i.e., transmit its signal) based on the input it received.

Output: The output from the activation function becomes the input for the next layer of neurons, and the process of weighted sum and activation function repeats until the final layer, which produces the network's output.

Error Calculation: The output generated by the neural network is compared to the actual target output (in supervised learning scenarios) to calculate the error or loss. This error is a measure of how well the network is performing on the given task.

Backpropagation: The error calculated in the previous step is used to update the weights of the connections in the network. This process, known as backpropagation, adjusts the weights in such a way that the network learns to minimize the error over time.

Training: The neural network undergoes training, where it iteratively adjusts its weights based on a training dataset to improve its performance on the task it's designed for.

Prediction/Inference: Once trained, the neural network can make predictions or perform inference on new, unseen data by passing the input through the network and generating an output based on its learned parameters.

Image segmentation

Image segmentation is a computer vision technique that involves dividing an image into multiple segments or regions based on certain characteristics such as color, intensity, texture, or boundaries. The goal of image segmentation is to simplify the representation of an image by partitioning it into meaningful and semantically coherent regions. These regions can then be used for various tasks such as object recognition, image analysis, or image editing.

There are several methods for image segmentation, including:

Thresholding: This method separates regions based on pixel intensity values. Pixels with intensities above or below a certain threshold are grouped into different segments.

Edge-based Segmentation: Edge detection algorithms are used to identify boundaries between different objects in an image. These boundaries are then used to segment the image into regions.

Region-based Segmentation: This method groups pixels into regions based on similarity criteria such as color, texture, or intensity. Techniques like clustering or region growing are commonly used for region-based segmentation.

Contour-based Segmentation: Contour detection algorithms are used to identify object boundaries, which are then used to segment the image into distinct objects or regions.

Semantic Segmentation: This is a more advanced form of segmentation where each pixel in the image is assigned a semantic label, such as "road," "car," "sky," etc. This type of segmentation is widely used in tasks like autonomous driving, medical image analysis, and scene understanding in computer vision.

Image segmentation plays a crucial role in various applications, including medical imaging (e.g., tumor detection), object detection and recognition in robotics and autonomous vehicles, image editing (e.g., background removal), and satellite image analysis, among others.

Image segmentation is the technique of subdividing an image into constituent sub-regions or distinct objects. The level of detail to which subdivision is carried out depends on the problem being solved. That is, segmentation should stop when the objects or the regions of interest in an application have been detected.

Segmentation of non-trivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. Segmentation procedures are usually done using two approaches – detecting discontinuity in images and linking edges to form the region (known as edge-based segmenting), and detecting similarity among pixels based on intensity levels (known as threshold-based segmenting).

Thresholding

Thresholding is one of the segmentation techniques that generates a binary image (a binary image is one whose pixels have only two values – 0 and 1 and thus requires only one bit to store pixel intensity) from a given grayscale image by separating it into two regions based on a threshold value. Hence pixels having intensity values greater than the said threshold will be treated as white or 1 in the output image and the others will be black or 0.

Viii. Result And Simulation

Image Processing Toolbox provides a comprehensive set of reference-standard algorithms and workflow apps for image processing, analysis, visualization, and algorithm development. Perform image segmentation, image enhancement, noise reduction, geometric transformations, and image registration using deep learning and traditional image processing techniques. The toolbox supports processing of 2D, 3D, and arbitrarily large images.

Image Processing Toolbox apps let you automate common image processing workflows. Interactively segment image data, compare image registration techniques, and batch-process large data sets. Visualization functions and apps let you explore images, 3D volumes, and videos; adjust contrast; create histograms; and manipulate regions of interest (ROIs).

Accelerate your algorithms by running them on multicore processors and GPUs. Many toolbox functions support C/C++ code generation for desktop prototyping and embedded vision system deployment.

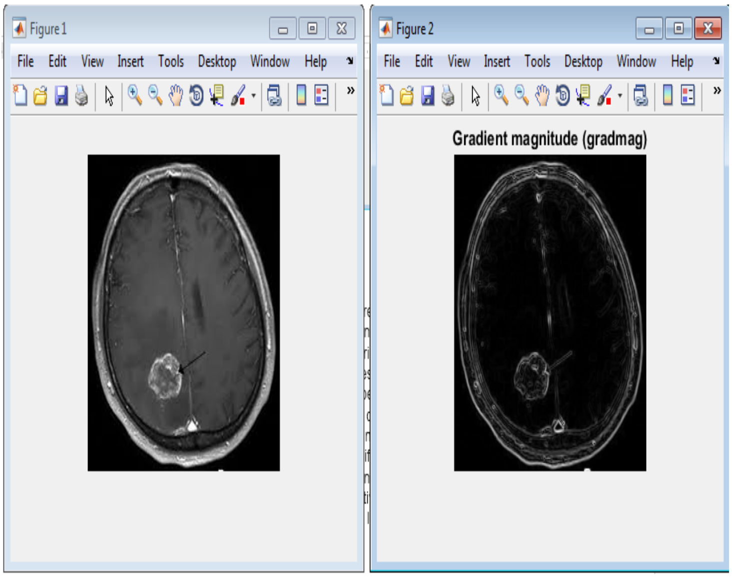

Fig.1. Data set image.

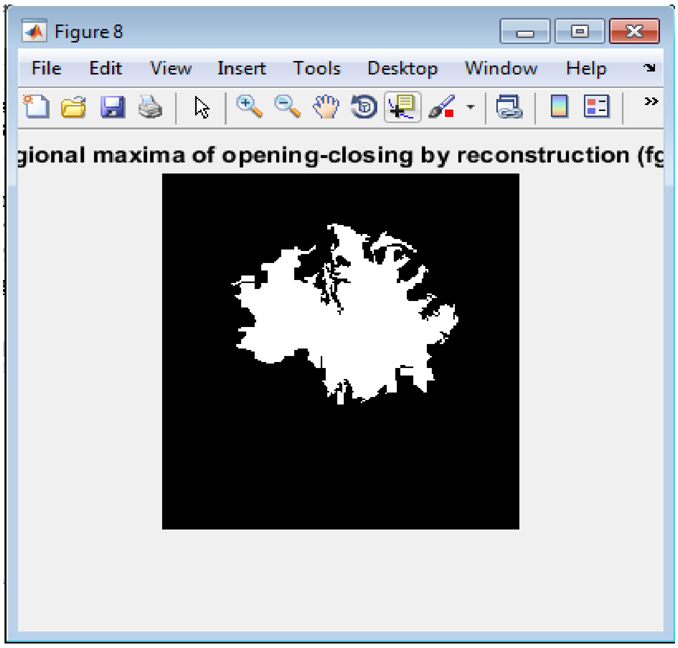

Fig.2. Segmentation image 1.

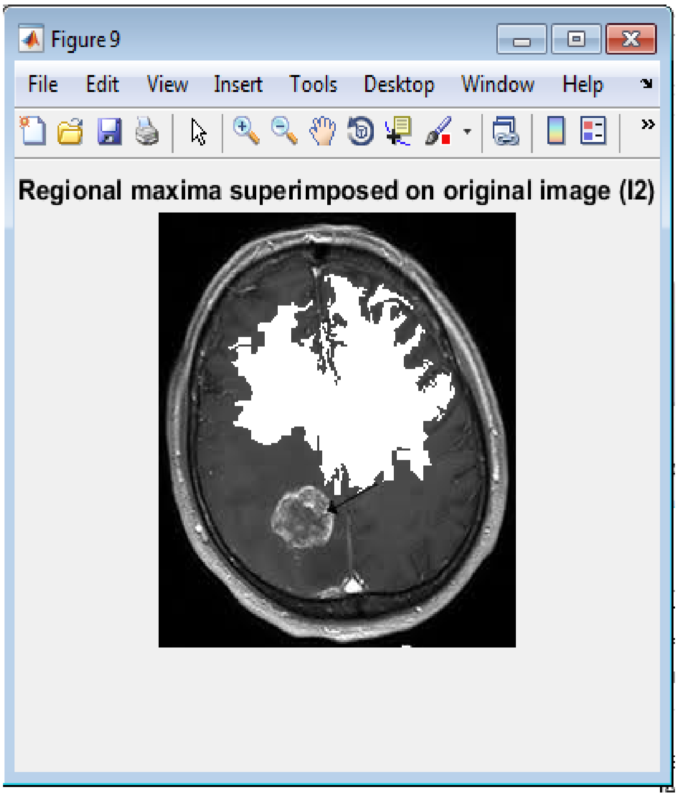

Fig.3. Segmentation image 2.

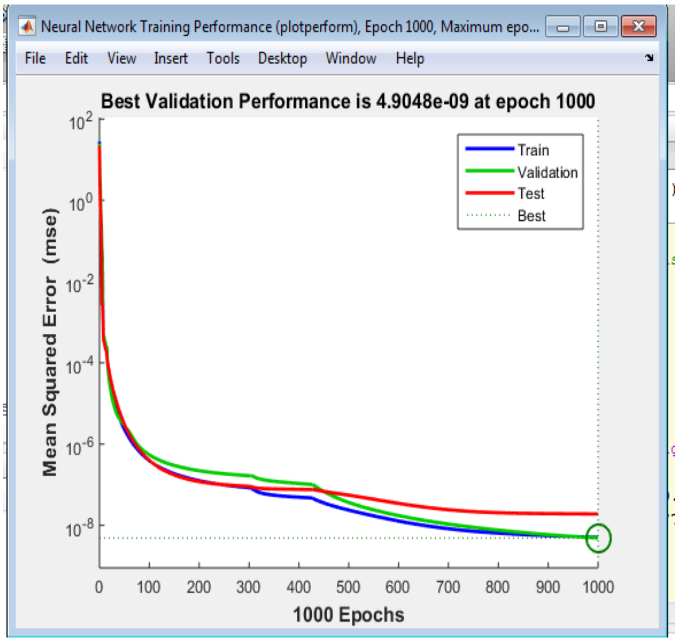

Fig.4. MSE Reduction.

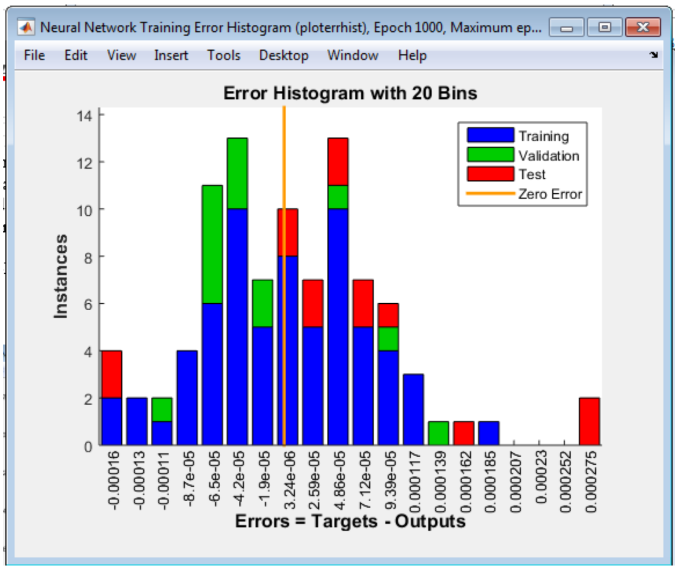

Fig.5.Satage of Accuracy variation.

IX. Conclusion

Our research proposes a set of optimal image quality enhancement strategies after conducting multiple sets of experiments through different combinations of image processing procedures such as noise reduction, sharpening, partial image color area homogenization, and color channel adjustment. After testing two public remote sensing scene image datasets on scene image classification task, it was shown that the image quality enhancement strategy proposed in this study can effectively improve the generalization performance of the deep learning model after training.

Medical imaging is a key technology that bridges scientific and societal needs and can provide an important synergy that may contribute to advances in each of the areas. Our survey has illuminated the current state of the art based on the recent scientific literature from 120 medical imaging research papers which may be beneficial to radiologists worldwide. In addition to finding that the ResNet architecture typically has the highest performance, we also covered the current challenges, major issues, and future direction

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