Hybrid Learning Model for Metal Artifact Reduction

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Abstract. In today’s healthcare, the human brain imaging is done for finding the tumors and other disorders of the brain. The Magnetic Resonance Imaging (MRI) plays a significant role throughout the complete clinical procedure starting from diagnostics and treatment planning to surgical processes and follow up studies. The MRI of brain allows the clinical expert for the earliest detection and treatment of brain abnormality or any neurological diseases, which is the most treatable stage that gives patients the greatest chance of survival. An artifact is a feature appearing in an image which is not present in the original imaged object. The types of artifacts are herringbone artifact, zipper artifact, motion artifact, aliasing artifact, chemical shift artifact, magnetic susceptibility artifact, central point artifact, Gibbs ringing artifact and intensity inhomogeneity artifact. After segmentation, the features are extracted using Gray level co-occurrence matrix (GLCM) and an CNN, Deep belief network, Proposed hybrid model (Based on CNN and Deep belief network (DBN)) and Morphological Technique with Segmentation Techniques is implemented to classify the brain MRI images as either normal (without tumor) or abnormal (with tumor). Proposed hybrid model for metal artifact reduction and represent though the experiment our proposed model very effective to existing one. Results in Accuracy (in %) Before artifact removal(92.12%), After artifact removal (95.77%)

Keywords: Convolution neural network, Magnetic Resonance Imaging, Support Vector Machine, deep learning

1. Introduction
The term “Medical image processing” (MIP) is the technique of developing algorithms for processing of medical images on a digital computer. It involves the development and implementation of problemspecific methods to enhance the quality of raw medical data (obtained from different modalities) for the determinations of specific visualization, further analysis and treatment planning. The MIP has undergone a dramatic growth and became an interdisciplinary research field by attracting expertise from computer science, engineering, mathematics, physics, biology, statistics and medical science. Now a days the computer-aided diagnostic and treatment planning has already become an important part of clinical procedure. The fastest growth, development and availability of high speed technological advancement and various modern imaging modalities has enabled to perform processing and analysis of a substantial volume of image data so that a quality image can be formed for diagnosis of disease as well as further treatment planning by medical expert. Human brain is the biggest and more complex
organ with a large processing capacity which is unmatched to any present computer system. It consists of over 100 billion nerves interacting as synapses in trillion links. The study of brain functions and information processing within is one of the greatest, interesting and challenging tasks in cognition. [1] The human brain performs controlling functions in our mind and body. The brain is made up of soft tissues and is protected by a very hard skull. The hard skull protects the brain from injuries. Along with hard skull, the brain is also surrounded by a layer of tissue called the meninges and cerebrospinal fluid (CSF) which fills the four ventricles in the brain and provides essential cushioning effect and also provides nutrients. Anatomically the brain is subdivided into three sections namely the forebrain, the midbrain and the hindbrain. The forebrain is made up of amazing brain, thalamus, hypothalamus and pineal gland. A part of the cortex stem is the midbrain (or mesencephalon) and is situated in the cortex core between the brain and backbrain. The anatomy of human brain as shown in Figure 1. The cortex is the out most layer of brain cells. The voluntary movements and thinking begin from the cortex.

2. Literature Review

The literature review is the wide-ranging survey and evaluation of reputed peer reviewed scholarly journal papers found in the literature connected to our research topic under study. This will provide a structural and theoretical base for our research work and will help to determine the nature of research outcome. Firstly, a detailed survey of various types of MRI artifacts that appear in brain MRI, their causes and possible remedies taken by the technician/radiologist is studied in detail. Secondly, a broad survey of MRI image segmentation methods is reviewed. Finally, a review of journal papers on artificial
neural networks for feature extraction, classification and detection of abnormalities in brain MRI image is done and summarized for our topic of the research work.

M U Ghani et al.[1] A new deep-learning approach to metal artifact. Subsequent full projection data is then used with traditional FBP to recreate an picture that is supposed to be free of objects. The latest technique results in an end-to-end metal artifact removal method that is computationally effective and thus realistic and blends right with current CT workflows, making it simple to use in current scanners. Deep network training can be difficult, and another contribution to our research is to show that the training data produced by accurate X-ray simulation can be used to effectively train the deep network when coupled with the transition of learning using small real data sets.

J Wang, J. H. Noble et al. [2] The segmentation of intra-cochlear anatomy structures (ICAs) in post-implant CT (Post-CT) photos of cochlear implant (CI) recipients is difficult due to the clear artifacts created by metallic CI electrodes. We suggest a multi-resolution, multi-task, deep network that synthesizes the artifact-free image and segments the ICAs in post-CT images simultaneously. The production value of the synthesis division is 1/64 of the production of the segmentation section. It eliminates the usage of memory for instruction thus creating high-resolution segmentation marks. In this preliminary analysis, we use the segmentation results of the automated approach as the ground truth to provide guidance to train our model, and we obtain a median index value of 0.792. Our experiments also confirm the usefulness of multitasking learning.

Du, M., Liang K. & Xing Y. [3] Artifacts in CT photos seriously impair clinical evaluation in diagnostic systems. Current error removal approaches model the physical dimensions of scanning and process artifacts appropriately. Metal artifacts are an important issue in this field. With the advancement of deep learning, it has been discovered that neural networks can identify the characteristics of objects. Here, we suggest a Cycle-GAN approach for the reduction of metal objects with the necessary non-paired marks, which allows it far simpler to function on realistic problems. We have validated our methods with practical CT data. From our preliminary results, our method demonstrated a strong and robust ability to reduce metal artefacts. In addition, the Cycle-GAN will produce CT images with actual objects at the same time, which will provide us with a data increase process.

Z. Zhang et al. [4] The care of tomosynthesis imagery may be influenced by two metal objects: undershooting and rippling. In this post, we suggest a new algorithm to reduce the effects of the metal objects (MAR). Second, raw projection specifics are measured and metal surfaces are segmented. The metal areas are then replenished with a meaning dependent on the (non-segmenting) pixels of the city. Filtered Backprojection (FBP) is then replicated separately for the filled regions and metal areas. Eventually, the two restoration findings are merged to create the final artifacts-free pictures. Phantom and realistic photographs are analyzed using qualitative and quantitative approaches that show the efficacy of the algorithms.

P Jin D. H. Ye and C. A. Bouman et al. [5] Segmenting interesting objects in CT images has a wide range of applications. Nonetheless, in order to obtain successful performance, it is always important to add metal artifact reduction to raw CT images prior to segmentation. While there has been a great deal of work focused on metal artifact removal and segmentation as separate projects, relatively few efforts have been made to address the two problems together. We are presenting a novel approach to solving Segmentation of raw CT photographs without accessing raw CT details with metal objects Considering the approximate Metal Mask, the issue is planned as a joint optimization of the restored image and the segmentation mark and the cost function consists of a dictionary picture before the regularization of the restored image. The subsequent optimization issue is solved by an effective alternative solution. The approach is used on both actual and simulated sets of data, and the findings demonstrate that it is efficient at minimizing metal errors while at the same time producing improved segmentation.
K. Inagaki and T. Tanaka et al. [6] When high-absorption content such as metal is present in the sample, the X-ray CT picture also includes objects that are irregular findings. This element is considered a metal piece. Metal artifact can be an obstacle to the accurate examination of objects. The item is then supposed to be minimized by the X-ray CT patient. Several techniques have been tested in attempts to minimize metal objects, but some approaches are not consistent with the form of the target and the elimination of metal artifacts. In this study, we used a method of discriminant analysis and sin curve interpolation. As a consequence, we might also delete metal objects and retain the form of the piece. Nevertheless, the cross artifact was left in the non-metal portion of the process.

Liao H., Lin et al. [7] Currently, a deep neural network technique for metal artifact reduction (MAR) computed tomography (CT) are managed approaches based on planning digital metal artifacts. However, since the effects of synthesis can not accurately reproduce the actual fundamental processes of CT imaging, supervised methods are also mistakenly utilized for clinical applications. To deal with this problem, we present the first unattended learning method to MAR to the best of our understanding. In particular, a new network of artifact detailings is being introduced which details CT images of metal objects in latent space. This promotes different modes of generation (object elimination, item relocking, self-reconstruction, etc.) and unique failure mechanisms in order to reduce the need for synthesized data surveillance. Extensive research reveals that our solution to metallic artifacts is far stronger than existing unattended models designed for standard image-to-image conversion problems when applied with a synthesized dataset and achieves comparable efficacy to current MAR models. Our approach is best adapted to generalizing controlled simulations as extended to clinical datasets.

3. Proposed Methodology

Hybrid model (Based on CNN and Deep belief network (DBN)) for metal artifact reduction. The Pipeline consists of several steps from the reception of raw data to the creation of the model ranking performance. As an input to the following level, any step output in the pipeline is supported. The approach pipeline is seen in the figure 2 and the details below are given.

- Data Acquisition: Data describes the role and provides a major contribution to model efficiency. We have used the necessary conversion and pre-processing of the images after receiving the brain tumor dataset, to enable the model work at its best.
- Data Pre-processing: Data collections of medical image are limited because of their constraints than those used in other fields. To optimize our run-time info, we used multiple augmentation techniques to generalize and generate high performance.
- Data Visualization: At the pre-processing and extension periods, we assembled the training data to get a feel of the trends.
- Model Creation: A model is an algorithm that recognizes data X and forecasts Y outcomes. We used the design of our model for the residual network.
- Model Training: Testing is the method by which the algorithm optimizes the parameters for the classification model and adjusts its weights.
- Model Evaluation: Our model was tested with precision, recall, consistency, f1-score and balance.
Deep learning is one of the most popular models of machine learning, initiated in the 1950s and researched extensively after approximately a neural network is made up of a series of linked computing units called layer neurons.

This are two of the many outstanding outlets for knowledge on neuronal neural networks as shown in figure 3. We can provide just a slight description of how they are designed and educated. The neural feedforward networks are parametric mathematical structures, the fundamental type of artificial neural networks.

But when complex networks are confronted with thousands or millions of parameters and an infinite amount of paths between the nodes and the network output, one easily faces huge computer challenges. It is rather difficult the strategies to overcome these challenges. Detailed description of the neural training networks methods and practical issues.

Hybrid model consist of linear and nonlinear functions. The multilayer or feed forward neural perceptron network, stemming from Rosenblatt’s work of the 1950s, is one of the simplest types of neural networks. It is based on simple, layered computing units called neurons. The performance of the jth unit on ith layer is \( z_j(i) = \text{total}(i)T_x \) for the ith layer and j for the jth unit on that line.

3.1 Segmentation Techniques

The segmentation techniques based on structural features are built on the spatial properties of an image, like edges or boundaries and regions. A number of edge detection procedures have been applied to brain images for extracting boundaries between different brain tissues. But these procedures are sensitive to noise and artefacts. The most popular structural technique is the region growing technique. In this process, one has to initiate the procedure by dividing an image into minor regions known as “seeds” The boundaries between neighbouring regions (seeds) are inspected. The strong boundaries are retained,
Poor restrictions are ignored and the respective areas combined. This is achieved on an iterative basis before no boundary is too poor to be refused. The solidity of the structural system depends on the collection of seed points and the proper description of regions. Segmentation models focused on statistical approaches grant marks to likelihood values dependent to intensity distribution of the picture pixels. The Gray-level thresholding is the effective and simplest approach. The threshold value is calculated using mean and standard deviation. [9] Here, a mark is applied to picture pixels by utilizing one or more color criteria when compare their gray tones. The picture is separated into only two parts, namely the backdrop and the foreground by a single threshold. During the last few decades, various segmentation methods of different accuracy and degree of complexity have been developed and implemented. Fast Fourier Transform (FFT) as shown in the figure 4. Here the most commonly used techniques or methods for image segmentation are listed below [10].

- Manual segmentation
- Intensity based methods (thresholding, region based, classification, clustering)
- Atlas based methods
- Surface based methods (active contours and surfaces)

![Figure 4. FFT input Image](image)

The original input image with herringbone artifact is taken from the data base. The application of FFT on input image will produce an output image frequency spectrum that shows the image details as well as artifact components appearing as bright spots. The edge detector of Canny is used to identify 'light spots,' which appear as objects, in the frequency spectrum of the original picture. The Canny boundary is based on the first derivative and the noise cleaning. [11] Detection of abrupt shifts in the frequency range is affected by the existence of objects.

3.2 Morphological Technique

Morphological procedures, often called mathematical mechanics, are used to segment brain MRI images. Morphology deals with the use of set theory principles to conduct image processing. It concerns the study of structures and shapes from a general scientific perspective. The dilation and erosion are the fundamental operations of morphological image processing. Morphological operations are typically conducted on discrete representations reflecting either 1 or 0 pixel values. Morphological filters are essentially non-linear transformations Altering the image's geometric properties. The morphologic filter transforms the original image into a second picture through an iteration process with another image of the appropriate size and shape referred to as the structuring element. The structuring factor is positioned in an picture at all practicable pixel positions and compared to the corresponding pixel region. [12] The amount of pixels from the picture artifacts is calculated according to the size and type of the structuring unit used for image processing. Adequate structuring element is used to perform morphological operations (dilation and erosion) to remove certain imperfections in the image[13]

4. Results Analysis

Signal to Noise Accuracy Segmentation and Noise Ratio measurement Before and after objects have been extracted with ground truth findings, 3D MRI details have been translated into 2D axial, coronary and sagittal slices and the most descriptive of 99 slices as illustrated resulting in 1400 images in each path. For each flow, ten-fold cross-validation is used to test the model’s stability. In each column the photos are separated by 75-25% split between training and evaluation into 10 subsets of about equivalent scale. The hybrid model is developed using the tensorflow backend keras library. The whole machine
requires roughly 30 minutes to train. In conjunction with The numbers refer to the depth of the model of each version. For separate batch sizes 8, 16 and 32 for 100 epochs, we often explore. This is, before changing network parameters, the amount of test sample used to learn. [14] The support vector machine with segmentation approach is used for optimisation through a learning rate of and a momentum value of 0.8. Table 1 displays the comparative Analysis obtained with from 10 times cross validation techniques for various batch sizes. The average accuracy achieved with in lot size to provide better accuracy than other variants. In addition, the thicker the layers increase the detailed classification. In terms of precision, we equate our idea with some of the latest multi-class evaluation systems focused on the techniques of research, and the findings are shown in. The precision reached with this approach is better than the standard system.

4.1 Accuracy

Accuracy for classification models is one of the most widely applied indicators. It is the sum of the accurate forecasts divided by the total number of forecasts. For an imbalanced dataset, we can get a high degree of precision that is mostly class-oriented. In an extreme case, each test case could be added to the large class by the classified to obtain a consistency equivalent to that of the most frequent marks in the test set. Precision can therefore be a deceptive measure of performance. The controlled precision is a better measure of generalizability. Where \( l \) is the class count, the average accuracy obtained on each class can be calculated.

\[
\frac{\sum (TP_i + TN_i) + (TP_i + FP_i + TN_i + FN_i)}{l}
\]

| Sample data set | Model                  | Accuracy (in %) Before artifact removal | Accuracy (in %) After artifact removal | SNR (in dB) Before artifact removal | SNR (in dB) After artifact removal |
|-----------------|------------------------|----------------------------------------|---------------------------------------|------------------------------------|-----------------------------------|
| Dataset1        | CNN                    | 78.33                                  | 88.90                                 | 55.201010                          | 57.34567                          |
| Dataset2        | Deep belief network    | 89.55                                  | 90.66                                 | 47.894500                          | 49.76474                          |
| Dataset3        | Proposed hybrid model  | 92.12                                  | 95.77                                 | 64.46677                           | 69.84848                          |

Magnetic resonance imaging is the most powerful and versatile medical imaging technique used in the medical field to acquire the detailed images of the soft tissue organs inside the human brain by noninvasive manner. But the MRI technique is susceptible to varieties of artifacts that occur during the time of image acquisition. The occurrence of undesired artifacts in desired images causes reduction in image quality and confuses the medical expert during pathology. Also segmentation of tumor in the presence of artifact reduces the accuracy of tumor segmentation. [15] This is because the artifact may obscure or hide the tumor resulting inaccurate segmentation. In this thesis work, a broad survey and study of the types of artifacts that occur during scanning of human brain using MRI scanner, the steps taken by the technician/radiologist to remove the artifacts or how to minimize them by adjusting the parameters of the scanner machine is done. [16] The expert radiologist suggested that some of the artifacts can be removed by them by rebooting the system and adjusting the related parameters of the scanner machine. However a few artifacts like zipper, herringbone, intensity inhomogeneity or bias field cannot be removed immediately by them. Such artifacts can be removed by developing image processing techniques. The results of the thesis work are analyzed and discussed with the expert radiologist and are found to be satisfactory. The techniques, methods and algorithms developed in this research work will assist the clinician/radiologist to remove herringbone artifact from brain MRI images, extract tumor region and in diagnosing the abnormalities present in the MR image of the brain.

5. Conclusion

Magnetic resonance imaging is the most powerful and versatile medical imaging technique used in the medical field to acquire the detailed images of the soft tissue organs inside the human brain by noninvasive manner. But
the MRI technique is susceptible to various artifacts that occur at the time of image acquisition. Proposed hybrid model (Based on CNN and Deep belief network (DBN)) and Morphological Technique with Segmentation Techniques is implemented to classify the brain MRI images as either normal (without tumor) or abnormal (with tumor). The occurrence of undesired artifacts in desired images causes reduction in image quality and confuses the medical expert during pathology. Such artifacts can be removed by developing image processing techniques. The results of the thesis work are analyzed and discussed with the expert radiologist and are found to be satisfactory. The techniques, proposed hybrid methods and algorithms developed in this research work will assist the clinician/radiologist to remove herringbone artifact from brain MRI images, extract tumor region and in diagnosing the abnormalities present in the MRI image of the brain.

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