Application of Machine Learning for Image Artefact Detection based on Computer Tomography Scanner

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Abstract

Theapplication of machine learning in solving complex medical and non-medical challenges keeps growing. The use of CT scanners is very crucial in saving lives hence the need to investigate alternative approaches for solving artefacts found in Computer Tomographic images. In some instances, such faultstakes a while to figure out the types of artefacts and their causes due to large datasheets. It is, therefore, against this background that such a study needs to be investigated. This paper makes use of 180 image datasets and feature detection is applied on each dataset (ring and metal) and both datasets are trained for both 25 and 50 epoch test. After completion of both epochs, unknown datasets are inputted into the model. This research results thus concluded that the model is efficient with an accuracy of 87% and 91% respectively for both 25 and 50 epochs based on 170 image datasets. Furthermore, for 88 image dataset, the results shows the model accuracy of 80% and 90% respectively for both 25 and 50 epochs. As a result, these results demonstrates the stability of the model and shows that the more images with higher resolutions are in a dataset, the higher the accuracy.

Keywords: *Artefact, Machine Learning, CT Scanner, Image Processing, Datasets.*
DOINumber:10.14704/nq.2022.20.8.NQ44660 NeuroQuantology2022;20(8):6368-6377

1. Introduction

In a contemporary healthcare approach, Computer Tomography (CT) images are widely been used for medical diagnosis and treatment purposes [1]. However, in the past few years, the world has seen many different approaches developed with the primary aim of improving CT image quality. This development has also spiked interest in Medical Imaging System (MIS) amongst the researchers within the computer vision community [2]. However, the term “artefact”in the context of this research paper, refers to any discrepancy or anomaly that is found within the captured CT image. This paper thus focuses on the two types of artefacts namely; Ring and Metal artefact.

This research paperpresents a machine learning-based approach for detecting image artefacts on CT images captured from Toshiba equipment. The final objective of this study is, therefore, to; 1) present an automated approachmodel for artefact detection; 2) To develop a machine learning-based model with capability to distinguish between metal and ring artefacts. To summarise, this article proposes an automated machine learning model developed on Kerasfor artefact detection, andproviding distinguishment between metal and ring artefact without any human interaction required.

The remainder of this paper is as follows. Section 2 provides the problem statement elaborating on the research question. Section 3 provides a discussion on the literature review on types of approaches already conducted in addressing artefact detection in medical imaging. Section 4 presents the systems modelling and development technique as well as the platform and application of machine learning techniques for data training. The results are outlined in Section 5 with accuracy testing between the trained data and tested data and the paper is concluded in Section 6.

2. Problem statement

Both medical and research institutions make use of standard-based troubleshooting procedures based on the equipment type and model. In most instances, technicians are prone to manufacturer-specific CT scanners and this results in a costly and time-consuming exercise that delays the medical attention to the patients.

It is for such reasons, that an automated artefact detection model with capabilities for artefact image detection and distinguishment model based on machine learning needs to be investigated, developed, and implemented to evaluate the feasibility and reliability of such a system in a live environment setup.

3. Literature review

In general, atefacts are caused by a range of sources and can degrade the quality of a CT image to varying degrees. However, the trend towards using machine learning is not only being driven by the need to increase diagnostic confidence but essentially by new clinical applications that create the potentialfor further academic and technical research.

This research paper makes mention of two types of commonly known artefacts namely ring and metal artefact. These artefacts have been investigated by a number of researchers such as Jinet al [3]. Subsequently, Dougherty et al.[4] present the medical imaging system for constructing an image in response to signals from diverse types of objects namely bodies and phantoms. Dougherty further highlights that medical imaging systems can be classified according to the radiation, and academic field of use. However, such applications are important in reducing the response time to save lives [5].

Huang et al. [6] presents a residual learning approach based on Convolution Neural Network (CNN) to reduce metal artefact in a cervical CTscans. Furthermore, Ghani et al [7] presents the data projection model utilisinga self-supervised sinogram framework. In contrast, Safdari et al [8] presents a technique for a new algorithm to reduce the metal artefact challenge by deploying five key steps in the algorithm namely a) extraction of metal region; b) filtration of the extracted metallic region; c) Segmentation and accurate extraction; d) utilisation of interpolation and 3) insertion of the corrected metallic section of the image to the original image. Additionally, Kyme et al [9] also investigate the best method to estimate and correct Single-Photon Emission Computer Tomography (SPECT), Positron Emission Tomography (PET) and CT images. In this study, Kyme makes use of motion fields within the modified reconstruction framework to obtain motion-corrected images.

3.1. CT Scanner basics

Figure 1 illustrates the operation of the third and fourth-generation scanners.

Figure 1. Test equipment being aligned (prepared for scanning) in the gantry aperture of a CT scanner.

Figure 1 depicts the preparatory scanning process for third and fourth-generation scanners. As indicated in Figure 1, the third-generation scanners are still in practice in most of the medical institutions of South Africa. Furthermore, the CT scanner in Figure 1 further illustrates the classification of a digital imaging system due to its use of computers to process images. This is important as a basis for radiographers and technicians to familiarise themselves with the functions and parts involved in making a CT scanner work.

4. Methodology

In the early days of image processing development, linear filters were used as the primary tools for image enhancement and restoration. However, due to the advancements in technology, other algorithms such as supervised learning multi-class classification logistic regression algorithm and linear regression algorithm are currently in use in the market. In this research study, the logistic regression algorithm is utilised.

4.1. Algorithm modelling approach

In themodelling process of the algorithm, two datasets are loaded into the model. Once this process has been completed, is important to augment the training dataset artificially by applying image augmentation to ensure stable results output. Augmentation code sneak peak is outlined below.

```
# this is the augmentation configuration we will use for training
train_datagen = ImageDataGenerator(
rescale=1. / 255,
shear_range=0.2,
zoom_range=0.2,
horizontal_flip=True)
```

Image dataset augmentation is accomplished by defining the image data generator parameters within the algorithm. The parameter settings are set as follows:

- Rescale —Each digital image is created by a pixel with a value between 0 and 255. 0 = black, 255 = white. So rescale the scales array of the original image pixel values to be between [0,1] which makes the images contribute more equally to the overall loss. Otherwise, higher pixel range image results in greater loss and a lower learning rate should be used, lower pixel range image would require a higher learning rate.
- Shear_range — The shape of the image is the transformation of the shear. It fixes one axis and stretches the image at a certain angle known as the angle of the shear.
- Zoom_range — The image is enlarged by a zoom of less than 1.0. The image is more than 1.0 zoomed out of the picture.
- Horizontal_flip —Some images are flipped horizontally at random.

Furthermore, an approach making use ofCNN is applied. CNN is designed for images that contain convolution layers that compare overlapping rectangular patches of the input to small learnable weight metrics "kernels/ filters" that encode features [10].

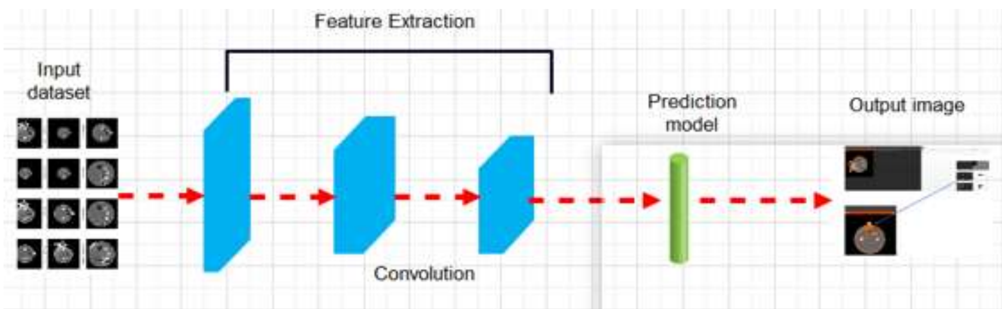

Figure 2. Convolution network layer output.

Figure 2 depicts the convolution network. The full convolution network comprises of the input dataset (metal and/or ring artefact). CNN architecture in the context of this research paper is based on layers of convolution. The convolution layers receive input and transform the input data from the image and pass it as input to the next layer. The transformation is known as the operation of convolution. However, it is critical to define the number of filters for each convolution layer. These filters detect patterns such as edges, shapes, curves, objects, textures, or even colors. The more sophisticated patterns or objects it detects are more deeply layered.

4.2. Implementation of image recognition and learning techniques for medical image systems

Machine learning algorithm was implemented using python programming language integrated with the following machine learning and computer vision-based algorithm and libraries such as 1) Keras; 2) TensorFlow, and 3) OpenCV.

- Tensorflow™ – this software is utilised as a machine learning software
- OpenCV – for image processing and detection
- Keras library – is a library interface for Tensorflow™ and is utilised as a supporting library for machine vision

These algorithms utilises a CUDA-based Graphical Processing Unit (GPU) that

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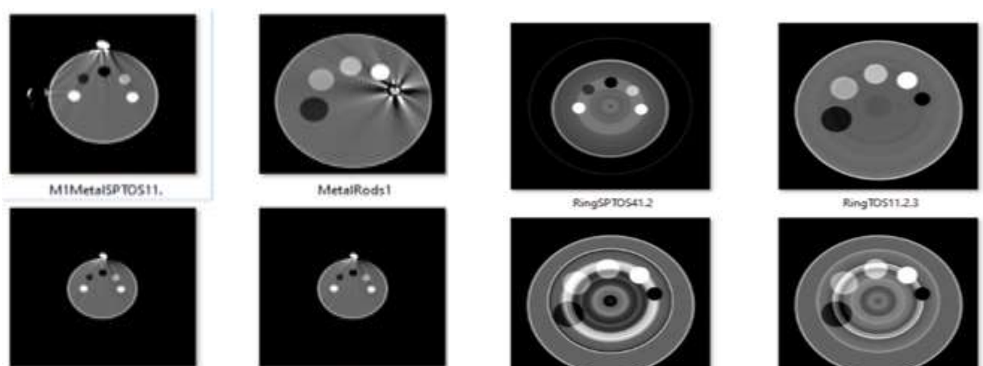
allows for parallel computing power provided by the GPU. The system implementation algorithm relied on the following system parts:

- AMD Ryzen 5 1600 3.4 GHz six-core processor
- NVIDIA GeForce GTX 1660 Ti 1.86GHz, 6 GB GPU
- 16 BB DDR4 RAM

The model frameworkdescribes the research project and how the data is collected. The data is collected by scanning image quality test equipment known as a phantom with Toshiba Medical Systems CT scanners. Upon noting the type of artefact, a folder is created and images are multiplied to reach 85 image samples, then copied into the folder per artefact type i.e (metal artefact and ring artefact). In this research paper, the researchers took 85 image samples per investigated artefact.

The system is trained and tested against a set of reconstructed image datasets. The system is trained on both 25 and 50-epoch tests using machine learning techniques. Upon the completion of the iteration, the system or model is tested and evaluated against the unknown data. The system model is evaluatedon the unknown data and this data is then used to determine the artefact type.



(a) (b)

Figure 3. (a) Metal artefact images 512x512 pixels; (b) Ring artefact images at 512x512 pixels.

In the collect and prepare data phase, the two images as outlined in Figures 3 (a) and (b) are copied into a single folder to create an image dataset. This image dataset comprises of raw data in which no filtering has been applied apart from enhancing the image brightness. The enhancement is done to allow for machine vision application for artefact detection without any system optimisation.

The training of the model is created to allow the model to learn by identifying the different features within an image and to automatically detect the artefacts. Figures 4 (a) and (b)presents the feature detection model for both metal and ring artefact.

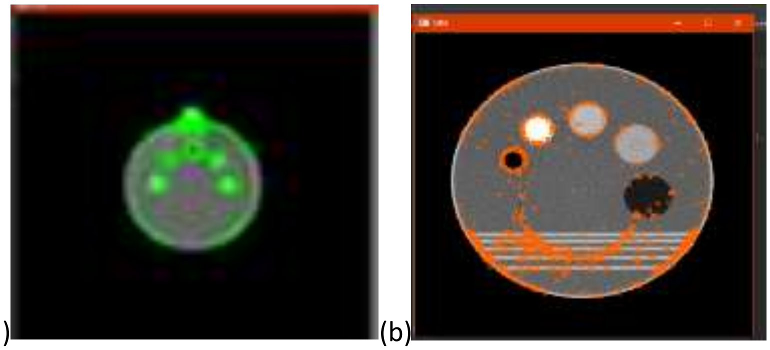
(a) (b)


Figure 4. (a) Metal artefact detection; (b) Ring artefact detection.

Figures 4 (a) and (b) depicts the metal and ring artefact detection in a model based on feature detection algorithm.Furthermore, ring artefact is seen by circles that formulates a smile-like face. Upon applying feature detection on the dataset for image detection purposes, convolution is then applied to both image datasets as indicated in Figure 5.

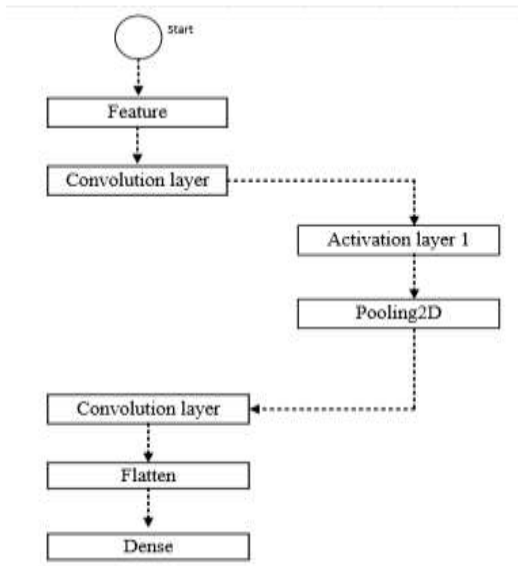


Figure 5. Model flow diagram.

Figure 5 depicts the model flow diagram. The features are applied to the model in the convolution layer. Upon the successful application of features, the process is highlighted at the activation layer and Pooling2D. Additionally, the features are also applied in the convolution layer, and the layer is placed at the flattening and dense mode and as a result, the modelling is achievable.

5. Results

Artefacts can seriously degrade the quality of CT images and in some instance to the point of making diagnostics unusable. However, to optimize image quality, it is necessary to understand why artefacts occur and how they can be prevented or suppressed. Hence the use of machine learning-based application is necessary for such applications.

However, the general approach in artefact evaluation makes use of analytic clinical data (patient scan). This approach is recommended to try to reproduce the artefact using a test phantom or just air in the scan field. However, this approach has let the conduction of this research

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paperthat aimedat developing an automated model that will be used to identify and detect different artefacts without any human intervention.

Table 1 presents the results of the paper based on the number of images within the dataset and also the epoch number.

Table 1. Model accuracy results based on 25 epoch for 170 and 88 image datasets.

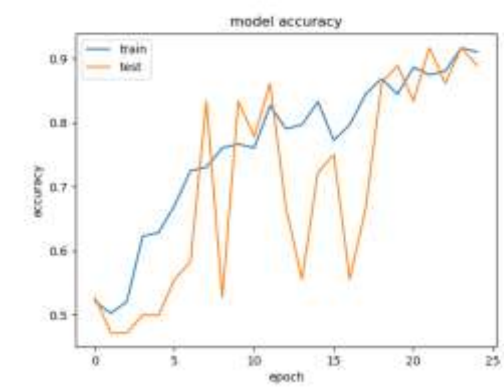
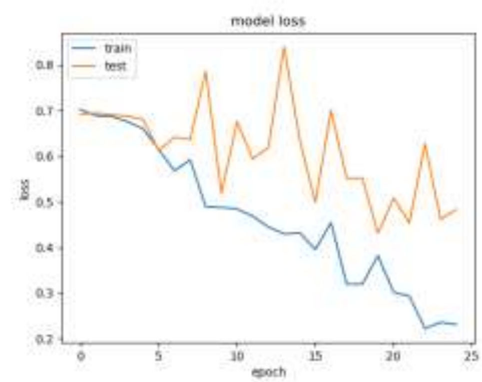
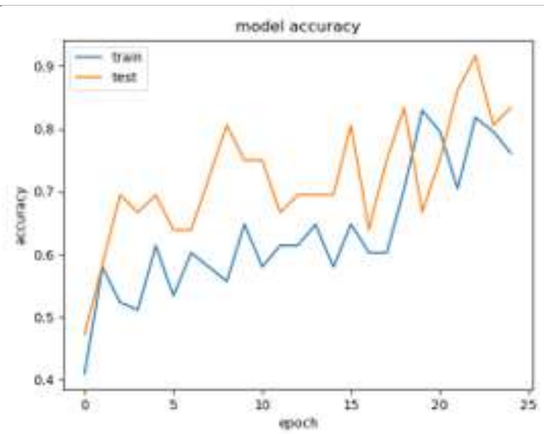
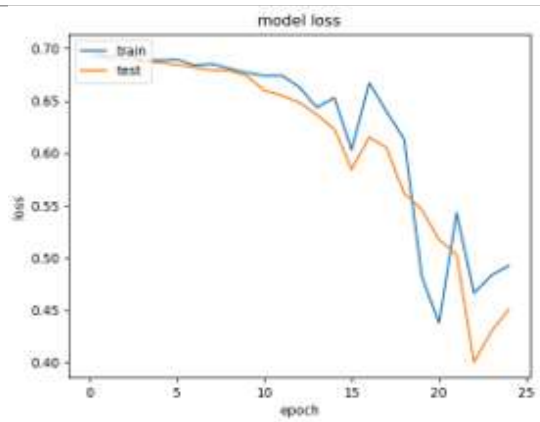
Model accuracy results	**Model loss graph**	**Results at 25 epoch**
		Trained Model 89% accuracy 21% Loss Testing model on test data 87% accuracy 49% loss
		Trained Model 75% accuracy 47% Loss Testing model on test data 80% accuracy 45% loss

Table 1 depicts model accuracy results for 25 epoch tests based on 170 and 88 image datasets. The results demonstrate that for a 25 epoch with 170 image dataset, the trained model the accuracy is 89% with 21% loss experienced. The testing model output results shows that the accuracy test is 87% with 49% loss. Furthermore, for 88 image dataset, the results demonstrates that the trained model accuracy is 75% with 47% loss, while the test model demonstrates 80% accuracy with 45% loss. Table 1 does demonstrate the stability of the proposed model for higher image datasets.

Table 2. Model accuracy results based on 50 epoch for 170 and 88 image datasets.

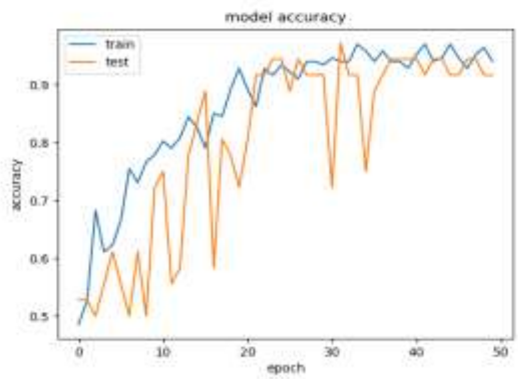
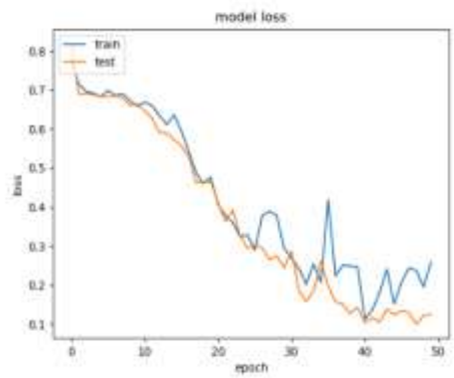
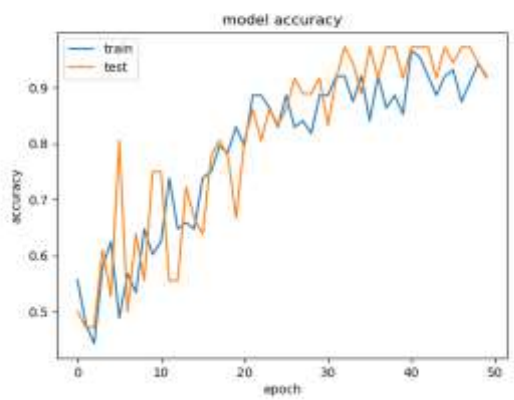
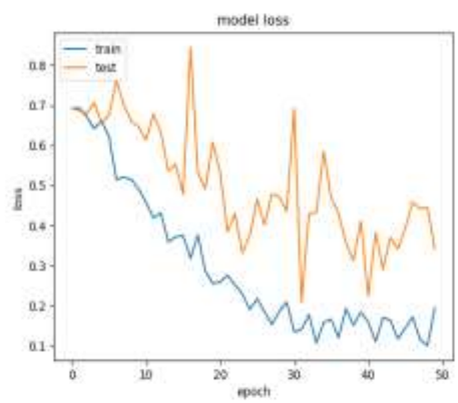
<table>
<tr><th>Model accuracy results</th><th>Model loss graph</th><th>Results at 50 epoch</th></tr>
<tr><td>
</td><td>
</td><td>Trained model
94% accuracy
21% Loss
Testing model on test data
91% accuracy
15% loss</td></tr>
<tr><td>
</td><td>
</td><td>Trained Model
91% accuracy
21% Loss
Testing model on test data
90% accuracy
31% loss</td></tr>
</table>

Table 3 depicts model accuracy results for 50 epoch test based on 170 and 88 image datasets. The results demonstrates that for a 50 epoch with 170 image dataset, the trained model the accuracy is 94% with 21% loss experienced. The testing model output results shows that the accuracy test is 91% with 15% loss. Furthermore, for 88 image dataset, the results demonstrates that the trained model accuracy is 91% with 21% loss, while the test model demonstrates 90% accuracy with 31% loss. Table 2 does demonstrate the stability of the proposed model for 88 image datasets with higher epoch tests.

6. Conclusion

The main goal of this research paper was to develop an automated machine learning-based model with the capabilities for artefact detection by comparing data from the trained model against the actual data from the testing model. This model was developed by capturing a total of 170 images comprising of 85 ring artefact and 85 metal artefact datasets. These image datasets were captured from Toshiba CT scanner and then a folder was created where the images were stored to create datasets. The machine learning model was then developed in python with each image having 512x512 pixels.

This research result has thus concluded that the model is efficient with an accuracy of 87% and 91% respectively for both 25 and 50 epochs based on 170 image datasets. Furthermore, for 88 image dataset, the results show the model accuracy of 80% and 90% respectively for both 25 and 50 epochs. Thes results demonstrate the stability of the model and alsoindicate that the more images with higher resolutions are in a dataset, the higher the accuracy.

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