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ja oivallusta
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Tekoäly on nopeasti kasvava ja kehittyvä ala ja koska tietokonetomografiakuvantamista käytetään paljon kaikkialla maailmassa, halusimme selvittää, millaista käyttöä tekoälyllä on TT:ssä. Teimme kirjallisuuskatsauksen kuudesta eri artikkelista, joista suurin osa liittyi konvoluutio-neuroverkoihin (CNN) tai muihin syvällisen oppimisen (DL) menetelmiin, kuten SCN.

Tekoälyä voidaan käyttää lääketieteellisessä kuvantamisessa ja TT:ssä monin tavoin, esimerkiksi tekoälypohjaisia sovelluksia voidaan käyttää potilaan paikannuksessa, parametrien valinnassa, skannauksen paikannuksessa jne. Tämän lisäksi havaitsimme, että tekoälypohjaisia sovelluksia ja erityisesti syvään oppimiseen perustuvia menetelmiä voidaan käyttää kohinan ja esineiden poistamiseen kuvista tai kuvien rekonstruoimiseksi, erityisesti pieniannoksisessa CT:ssä. Kaikkia näitä tekoälymenetelmiä voidaan mahdollisesti käyttää potilaan säteilyannoksen vähentämiseen kuvan laadusta tinkimättä.

Tekoälyä voidaan käyttää myös auttamaan radiologeja havaitsemaan leesioita tai kasvaimia kuvista. Kaikki tämä tarkoittaa sitä, että tekoälyn käytön edut TT:ssä ovat valtavat ja koko ajan nopeasti kehittyvän tekniikan ansiosta hyödyt varmasti vain kasvavat. Näille sovelluksille on kuitenkin edelleen rajoituksia, kuten laskentatehoon ja prosessointiaika kysymyksiin liittyen. Myös joillain sovelluksilla oli joitakin ongelmia hämärtymisen kanssa.

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Artificial intelligence is a vastly growing and developing field and due to the high use of computed tomography imaging worldwide, we wanted to find out what kind of uses AI has in CT. We did a literary review of six different articles, most of which were related to convolutional neural networks (CNN) or other deep learning (DL) methods like SCN.

We found that the uses of AI in the field of medical imaging and in CT are many, for example AI-based applications can be used to help in patient positioning, parameter selection, scan positioning etc. In addition to that, we found that AI-based applications and more specifically deep learning based- methods can be used to remove noise and artifacts from images, or to reconstruct images, especially succeeding in Low-dose CT.

All these AI-methods can possibly be used to reduce a patient's radiation dose without sacrificing image quality. AI can also be used in helping radiologists to detect lesions or tumors from images. All of this means that the benefits of AI use in CT are immense and due to technology rapidly developing all the time, the benefits will surely only grow. There are still limitations to these applications though, like computational power and processing time issues, as well as some blurring issues with some.

Keywords	Computed tomography (CT), Artificial intelligence (AI), Convolutional neural network (CNN)

Sisällys

1 Introduction

The use of computed tomography (CT) has quickly grown in recent decades because it allows for visualization of anatomical structures with high temporal and spatial resolution. However, with the substantial amount of CT scans being performed every year, the ionizing radiation implicit to CT has become a concern. Therefore, there has been growing interest in dose reduction in CT examinations. (Lee – Seeram 2020.)

In computed tomography, artificial intelligence (AI) can enable further reductions in patient radiation dose through automation and optimization of data acquisition processes, including acquisition parameter settings and patient positioning. After data collection, optimization of image reconstruction parameters, image denoising methods and advanced reconstruction algorithms can enhance many aspects of image quality, especially by reducing image noise and allowing for the use of lower radiation doses for data acquisition. In addition, AI-based methods that can automatically segment organs or detect and characterize pathology have been brought into clinical practice to bring automation, increased sensitivity, and new clinical applications to patient care, increasing the benefit to the patients. In conclusion, since the introduction of CT, many technical advances have enabled increased clinical benefit and decreased patient risk, not only by reducing radiation dose, but also by lessening the probability of errors in the performance and interpretation of medically justified CT examinations. (McCollough – Leng 2020.)

The main theme of this thesis project is ‘AI based solutions in computed tomography’. We chose this theme because AI-technology is rapidly developing, and it will influence radiographers’ and radiologists’ work more and more in the future. Also, in addition to this thesis we were involved in an innovation project with a similar theme. That project was done in a multi-national and multi-professional group and it inspired us to choose this subject for our thesis and helped us to get familiarized with it.

In this thesis, we plan to map out and review several different articles about artificial intelligence-based solutions in CT imaging, mainly those related to CNN. We want to find out what kind of solutions there are already in use and what their main benefits and disadvantages are. We will only select scientific articles that have been written in the past five years, are written in English and have been peer reviewed.

2 Abbreviations

3D= Three-dimensional

AI= Artificial intelligence

ANN= Artificial neural network

CT= Computed Tomography

CNN= Convolutional neural network

DCNN= Deep convolutional neural network

DL= Deep learning

GPU= Graphics processing unit

HU= Hounsfield unit

ICT= Information and communications technology

ML= Machine learning

IR= Iterative reconstruction

FBP= Filtered Back Projection

MBIR= Model Based Iterative Reconstruction

ASIR= Adaptive statistical iterative reconstruction

AEC= Automatic exposure control

DLR= Deep learning reconstruction

SNR= Signal-to-noise ratio

ROI= Region of interest

PSNR= Peak signal to noise ratio

MSE= Mean squared error

RMSE= root mean-square-error

SSIM= structural similarity

MAP-NN= Modularized adaptive processing neural network

3 Computed tomography

Computed tomography, CT for short, is an imaging system that uses a narrow beam of x-rays to produce signals which are then processed by the machine's computer to produce cross-sectional images ("slices") of the human body. These images contain much more information than regular x-ray images and they can also be digitally put together by the machine's computer to form a 3D image. (National Institute of Biomedical imaging and Bioengineering, 2019.)

In CT, x-rays are emitted from multiple angles and the detectors in the scanner measure the difference between x-rays that are passed through the body and x-rays that are absorbed. This is called attenuation and its amount is determined by the density of the imaged tissue. Different tissues are assigned a Hounsfield Unit (HU) or a CT number. Tissues with strong absorption (high attenuation coefficients) have a high Hounsfield value and are white in the image, while tissues with weak absorption (low attenuation coefficients) have a low HU value and are black in the image. Air has a HU of a -1000, fat has one of -70, water has a value of 0, blood has one of 70 and bone has the highest value of 1000. (Barnes – Quach 2018.)

Computed tomography is an ideal imaging modality in emergency cases because of its ability to get detailed information in a very short amount of time. But CT is also a valid option when wanting to identify different diseases or injuries in a non-emergency case. It can be used to image any part of the body, but it has become an especially good tool in detecting possible lesions or tumors in the abdomen, abnormalities in the heart, clots or bleeds or tumors in the brain, excess fluid or pneumonia in the lungs and specifically complex bone fractures or eroded joints. (National Institute of Biomedical imaging and Bioengineering 2019.)

3.1 Radiation doses in computed tomography

When radiation passes through the body, the x-rays that are not absorbed are used to create the image and the radiation amount that is absorbed, counts to the patient's overall radiation dose. (Radiologyinfo.org 2020.)

Due to its isotropic spatial resolution at 0.3–0.4 mm and fast scanning speeds, CT has established itself as a primary diagnostic imaging module in the last two decades. It allows doctors and radiologists to diagnose diseases and injuries more quickly, precisely and more safely. Still, a potential risk of radiation-induced malignancy exists, as it does in all radiation induced imaging. So, naturally every single CT examination must be appropriately justified by clinicians and radiologists for each individual patient. Also, for each examination, all technical aspects must be optimized, so that the required level of image quality can be acquired while keeping the dose as low as possible. (Yu – Liu – Leng – Kofler – Ramirez-Giraldo – Qu – Christner – Fletcher – McCollough 2009.)

Radiation doses in computed tomography can be calculated in many ways, for example scanner radiation output which is represented by CT dose index (CTDIvol), organ dose (specific radiation risk on an organ) and effective dose which is usually expressed by the units of mSv and represents the whole body dose. (Yu et al., 2009.)

The approximate effective dose of a normal chest CT is 7 mSv, which compares to about 2 years of natural background radiation, whereas the effective dose of a normal chest x-ray is only 0.1 mSv. The approximate effective dose of a head CT is 2 mSv and it's comparable to about 8 months of natural background radiation. The dose for an abdomen and pelvis CT is 10 mSv, which compares to 3 years of natural background radiation. But repeating that same examination with and without contrast agent, shoots the effective dose up to 20 mSv. (Radiologyinfo.org 2020.)

Though the ALARA principle should always be considered, radiation dose should only be reduced if the diagnostic image quality isn't sacrificed. Therefore, to understand how to reduce the radiation dose in computed tomography, it is important and necessary to be familiar with the relationship between image quality and radiation dose. (Yu et al., 2009.)

The following are the general principles of ALARA: justification, optimization and limitation. Justification means that the exam needs to be medically indicated. Optimization means that the exam must be done using doses as low as reasonably achievable (ALARA), while consistent with the diagnostic task. The third one, limitation, means that while dose levels to people who are exposed to radiation through work (for example radiologists and technologists) are limited to levels which are recommended by organizations, those same limits are not typical for medically necessary procedures or exams. (McCollough – Primak – Braun – Kofler – Yu – Christner 2009.)

3.2 Dose reduction strategies in CT

Thanks to the increasing number of CT exams, radiation exposure to society has significantly increased since its introduction. There are ways of reducing that dose, however, and the most important way to reduce CT-radiation exposure is to use dose-reduction techniques including tube current modulation, organ-specific care, beam-shaping filters, and most importantly optimization of CT parameters. Fundamental parameters of every

CT protocol include tube current (mA), tube voltage (kV), pitch, voxel size, slice thickness, reconstruction filters, and the number of rotations. It's very important to realize that a different combination of parameters enables different image qualities while delivering the same radiation dose to the patient. (Willemink – Noel 2018.)

Unlike traditional radiographic imaging, a CT image never really looks "over exposed" so, it's neither too dark nor too light. The nature of computed tomography data makes certain that the image always appears properly exposed. Hence, CT users are not technically obliged to decrease the tube-current-time product (mAs) for smaller patients, which might result in a larger radiation dose for these patients. It is, however, an important responsibility of every CT operator to take patient size into account when selecting the parameters that affect radiation dose, the most basic of which is the mAs. (McCollough et al., 2009.)

Tube potential and tube current exposure time can both be altered in computed tomography to give the appropriate exposure to each individual patient. However, users most commonly standardize the tube potential (kV) and gantry rotation time (s) for a given clinical application. The fastest rotation time is mostly used to minimize artifact and motion blurring. Also, the lowest kV consistent with the patient size should be selected to maximize image contrast. (McCollough et al., 2009.)

3.2.1 Iterative Reconstruction (IR)

Advances in computing power have allowed for the development of software-based methods for iterative image reconstruction (IR) in computed tomography. The most common technical principle of IR algorithms is reconstructed image data by application of filters based on statistical data models or mathematical models of the CT imaging process and/or the iterative improvement of measured projection. Compared to filtered back projection (FBP) these IR algorithms enable the reduction of image noise and the improvement of overall image quality. Since noise and overall image quality are directly linked to the radiation exposure, a reduction or suppression of noise via the application of IR algorithms consequently allows for a reduction in patient dose. (Stiller 2018.)

The primary idea of IR is the calculation of image data truly corresponding to acquired projection data. When applying the mathematical definition of an iterative algorithm to CT image reconstruction, an ideal IR process is made up of a cycle of forward and back projection steps with repeated transition from projection, which is the raw data, to image space and vice versa, iteratively improving reconstructed image data in the process. The forward projection step produces synthetic projection data that is compared to measured projection data. The back-projection step cultivates a correction determined from the difference of simulated and measured projections to image space where it is applied as an update to the current image data estimate. An ideal IR method therefore consists of the following steps; (1) Based on an initial image estimate, synthesized projections are simulated by forward projection (transition from image to projection space). (2) By comparison of synthesized projections to measured projections a correction term is calculated from their difference. (3) The current image estimate is updated by back projection of the correction term (transition from projection to image space). (Stiller 2018.)

3.2.2 Filtered back projection (FBP)

Filtered back projection (FBP) has been the standard of reference for reconstructing CT image data for the past four decades. Due to the relatively low complexity of the underlying linear transformation from projection space (raw data) to the image space, aka the back projection, the method is fast and strong and only requires limited computing power for CT image reconstruction. Before back projection, calculated projections are first convoluted with a so-called kernel or kernel, controlling the characteristics of reconstructed image data. The filter is necessary to make up for the blurring, which results from nonuniform data sampling essential to the CT acquisition process and restores or enhances the edges of the structures of the imaged object. Filter choice has a direct influence on spatial resolution and image noise, with higher filtration enabling a better definition of edges and a clearer delineation of structural detail but enabling an indirect increase in image noise. In clinical practice, several kernels with different characteristics are available. ‘Soft’ kernels, which reduce image noise but impair image sharpness optimized for visualization of low-contrast detail, and ‘sharp’ kernels, which enhance the depiction of fine details in structures of high contrast but are subject to high levels of image noise impairing detectability and delineation of low-contrast structures. After the sorting of filtered projections into sinograms, these are then back projected to image space along parallel rays by equally distributing measured total attenuation to the pixels of the image matrix (voxels of the image volume). CT image data thus reconstructed are the sum total of all back projected filtered attenuation profiles. (Stiller 2018.)

4 Artificial intelligence

The term Artificial intelligence (AI) is used on machines and software that mimic human-like cognitive abilities like learning and problem-solving skills. Most often when we think of AI, we are referring to computer sciences which is trying to program systems that can perform tasks that usually need humans to operate. With advances to computers' computational power, development of more advanced AI's has been possible. This has led to an increased use of AI in healthcare. In the last ten years the amount of research about AI uses in healthcare has risen from 100 papers in a year to almost 1000. 50% of medical AI research is for CT and MRI. AI research is making huge impact in radiology by being the source of major innovations. (Pesapane – Codari – Sardanelli 2018.)

In 1956, a group of computer scientists suggested that computers could be programmed to think and to reason. Also, that learning, or any other kind of intelligence could, in theory anyways, be so precisely described that a machine could simulate it. They described this principle as artificial intelligence. So, simply put, AI is a field focused on automating intellectual tasks usually performed by humans, and machine learning (ML) and deep learning (DL) are specific methods of getting to this goal. (Choi – Coyner – Kapalthy-Cramer – Chiang – Campbell 2020.)

However, AI also includes techniques that don't really involve any form of learning. For example, the subfield known as symbolic AI focuses on hardcoding rules for every possible scenario in a field of interest. These rules, written by humans, come from a priori knowledge of the subject and task to be completed. For example, if one were to program an algorithm to modulate the room temperature of an office, they likely already know what temperatures people are comfortable working in. So, they would program the room to cool if temperatures rise above a specific temperature and heat if they drop below a specific temperature. This kind of symbolic AI is good at solving clearly defined logical problems, but it often fails to perform tasks that require a higher-level of pattern recognition. These more complicated tasks are where machine learning and deep learning methods perform much better in. (Choi et al., 2020.)

4.1 Machine learning (ML)

Machine learning (ML) is a subfield of AI. Machine learning is enabling systems to learn from data without it been specifically programmed for it. Computational models and algorithms create a network of nodes, an artificial neural network (ANN), which works like the neural networks of the human brain. These networks consist of numerous interconnected nodes. Each node has a differently weighted value for data that goes through them and it’s this data that activates or deactivates them. Nodes are categorized in three layers, which are input, output and hidden layer. The Input layer receives data, the output layer is nodes processed data and the hidden layer refines calculations and reads patterns from data. Machine learning uses input-and output layers and the data inputted is labeled and its variables are predefined. An example for ML use is clinical stress-testing and imaging variables to predict major adverse cardiac events (MACE). (Pesapane – Codari – Sardanelli 2018.)

In training phase these nodes are taught how to react and to what data. There are three types of learning techniques: supervised-, semi supervised- and unsupervised learning. With supervised learning techniques all data used is labeled, which means that all the needed detail is known. For example, in a bone x-ray there is s label that tells if the bone is fractured or not. Semi supervised learning uses labeled and unlabeled data. In this technique labeled data acts as a guide and unlabeled data refines/enhances the result. Unsupervised learning uses only unlabeled data. Algorithms are given large quantities of data to process. Then the algorithms start to find patterns from data and divide them to groups, for example images of brains with metastases and those without. Advantages of unsupervised learning is that algorithms learn to recognize finds that humans can't see yet. (Quantib, The ultimate guide to AI in radiology, nd.)

4.1.1 Supervised Learning

Supervised learning uses patterns in a training dataset to map specific features to a specific target so that an algorithm can make predictions on future datasets. This approach is supervised because the model concludes an algorithm from feature-target pairs and is informed, by the target, whether it has predicted correctly or not. The basic steps of supervised machine learning are; (1) acquiring a dataset and splitting it into separate training, validation, and test datasets; (2) using the training and validation datasets to inform a model of the relationship between all the features and the target; and

(3) evaluating the model via the test dataset. In each of these situations, the performance of the algorithm on the training data is compared with the performance on the validation dataset. The most usual supervised learning tasks are classification and regression. Classification involves predicting to which category an example belongs and regression, on the other hand, involves predicting numeric data, such as test scores, laboratory values, or prices of an item. (Choi et al., 2009.)

4.1.2 Unsupervised Learning

Unlike supervised learning, unsupervised learning aims to notice certain patterns in a dataset and categorize individual instances in the dataset to said categories. The reason why the algorithms are unsupervised is because the patterns that might or might not exist in a dataset are not informed by a target but are instead left to be determined by the algorithm itself. Some of the most common unsupervised learning tasks are association, clustering and anomaly detection. (Choi et al., 2009.)

4.1.3 Semi-supervised Learning

Semi-supervised learning can be thought of as a sort of medium between supervised and unsupervised learning and it’s particularly useful for datasets that contain both labeled and unlabeled data. This situation typically arises when labeling images either becomes cost-prohibitive or time-intensive. Semi-supervised learning is often used for medical images, in cases like, when a physician labels a small subset of images and then uses them to train a specific model. This model is then used to classify the rest of the unlabeled images in the dataset. (Choi et al., 2009)

4.1.4 Reinforcement Learning

Reinforcement learning is the technique of training an algorithm for a specific task where no one answer is correct, but an overall outcome is wanted. So, it’s the closest attempt at modeling the human learning experience as possible because it also learns from trial and error rather than just data alone. Although reinforcement learning is a powerful technique, its applications in medicine are currently limited and thus it has yet to make a substantial impact in clinical medicine. It has however, its place in the field of computer science and machine learning. (Choi et al., 2009.)

4.2 Deep machine learning (DL)

Deep learning is a subgroup of machine learning with the main difference being that DL uses deep neural networks that have hidden layers between input and output layers to refine calculations and predictions. Deep neural networks can use an image as an input directly when simple neural networks need pre-processing to derive the image features which will be the input for the data. (Quantib. The ultimate guide to AI in radiology, nd.)

The deep learning approach was developed to improve on the performance of conventional artificial neural networks (ANNs) when using deep architectures. A deep ANN is different from the single hidden layer by having many hidden layers, which distinguishes the depth of the network. Amidst these different deep ANNs, convolutional neural networks (CNNs) have become more popular for example in computer vision applications. In convolutional neural networks, convolution operations are used to obtain feature maps in which the intensities of each pixel/voxel are calculated as the sum of each pixel/voxel of the original image and its neighbors, weighted by convolution matrices, which are also called kernels. Different kernels are applied for different specific tasks, such as edge detection, blurring or sharpening. CNNs are biologically inspired networks imitating the behavior of the human brain, which contains a complex structure of cells sensitive to small regions of the visual field. The architecture of deep CNNs allows for the formation of complex features, such as shapes, from simpler features, such as image intensities, to decode image raw data without the need to detect specific features. (Pesapane – Codari – Sardanelli 2018.)

Success in deep learning applications has been possible mainly due to the recent advancements in the development of hardware technologies, like graphics processing units. The high number of nodes required to detect complex patterns and relationships within data may result in billions of parameters that need to be optimized during the training phase. For this reason, DL networks require a huge amount of training data, which in turn increase the computing power needed to analyze them. These are the reasons why DL algorithms are showing increased performance and are, theoretically, not susceptible to the same performance plateau as the more simpler machine learning networks. (Pesapane – Codari – Sardanelli 2018.)

DL algorithms' data-driven approach allows for more abstract feature definitions, making it more universal and informative. Deep learning can thus automatically measure phenotypic characteristics of human tissues, promising great improvements in diagnosis and clinical care in radiography. DL has the added benefit of reducing the need for manual preprocessing steps. For example, to extract predefined features, accurate segmentation of diseased tissues by professionals is often needed. Because deep learning is data driven though, with enough example data, it can automatically identify diseased tissues and hence avoid the demand for expert-defined segmentations. Given its ability to learn complex data representations, DL is also often strong against undesired variation, such as the inter-reader variability, and can therefore be applied to a large variety of parameters and clinical conditions. In a lot of ways, deep learning can mirror what radiologists do; identify image parameters but also weigh up the importance of these parameters based on other factors. (Hosny – Parmar – Quackenbush – Schwartz – Aerts 2018.)

5 Convolutional neural network (CNN)

Convolutional neural networks are a type of a deep learning model for processing data that has a grid pattern, like images. It is inspired by the organization of animal visual cortex and designed to automatically and adaptively learn spatial hierarchies of features, from low-level to high-level patterns. (Yamashita – Nishio – Do – Togashi 2018.)

CNN is a mathematical construct that is typically composed of three types of different layers: convolution, pooling, and fully connected layers. The first two, convolution and pooling layers, perform feature extraction. The third, a fully connected layer, maps the extracted features into a final output, such as classification. A convolution layer plays a key role in CNN, which is comprised of a stack of mathematical operations, such as convolution, which is a specialized type of linear operation. (Yamashita – Nishio – Do – Togashi 2018.)

In digital images, pixel values are deposited in a two-dimensional (2D) grid. Then a small grid of parameters called a kernel is applied at each image position. This makes CNNs highly efficient for image processing, since a feature may take place anywhere in the image. When one layer sends its output into the next layer, extracted features can hierarchically and progressively become more intricate. The process of optimizing parameters such as kernels is called training, which is carried out to minimize the difference between outputs and ground truth labels through an optimization algorithm called back-propagation and gradient descent. (Yamashita – Nishio – Do – Togashi 2018.)

6 Uses of AI in CT

The idea of applying artificial intelligence to medical imaging is interesting for many reasons. First, it is becoming clear that image datasets harbour a great deal more useful data than a human can normally process. Secondly, simple tasks, like subsequent measurements and drawing contours, can be performed by computers more consistently, without interference and a lot faster than humanly capable. Although the development of useful machine learning (ML) models will take time, it is suggested that the implementation of AI will enable physicians to start working more efficiently. (Siegersma – Leiner – Chew – Appelman – Hofstra – Verjans 2019.)

When it comes to medical imaging, AI impacts all steps of the imaging chain. The first step is giving decision support for the selection of the suitable diagnostic imaging modality. Presently, healthcare is continuously pushing towards evidence-based decision-making and the use of guidelines. AI-based decision-support tools can help in the selection of the most appropriate imaging exam for individual patients. Additionally, vendors are currently selling commercial products that implement ML during the examination of a patient. AI is implemented in image reconstruction as well, for example when using low-dose computed tomography to obtain an optimal anatomical reconstruction, image interpretation and diagnosis. (Siegersma et al., 2019.)

6.1 Patient positioning

A physical object, referred to as a ‘bow-tie filter’, is used to lessen the number of x-ray photons hitting the edges of the patient, because the patient’s thickness is smaller there and so, fewer photons are needed. Patients are thickest at the isocentre, so naturally, the filter has the lowest amount of attenuation there. Especially for patient dose optimisation, the bow-tie filter is a paramount tool. However, if the patient is not centred around the isocentre correctly, there is discrepancy between the assumption used in developing the bow-tie filter and the actual patient set-up. This can cause the radiation dose to be misapplied in some body locations, and image noise is increased relative to when the patient is positioned at the isocentre. (McCollough – Leng 2020.)

For a while now, all CT systems have incorporated a feature, referred to as automatic exposure control (AEC), which is used to decrease the tube current for a patient's thinner body regions and to increase the tube current for the thicker body regions. For the system to estimate the right attenuation of a specific body region, it depends on the information provided by the CT localiser image. If the patient is positioned too high or too low with respect to the isocentre, the system perceives the patient as being either too thin or too thick, respectively. This is because the spatial calibration of a CT system is performed at the isocentre. (McCollough – Leng 2020.)

More recently, a certain CT manufacturer has also integrated a 3D infra-red camera into their CT system. The camera is located on the ceiling of the imaging room, above the patient table and it produces a three-dimensional image of the patient's surface with depth information. Then, using an AI algorithm, it detects specific landmarks on the patient's surface and based on the portion of the body to be scanned and the current height of the table, the system automatically moves the table vertically to position the patient such that the majority of the scanned anatomy is located at the correct isocentre, reducing errors in patient positioning significantly. (McCollough – Leng 2020.)

6.2 Scan positioning

Once a specific patient is centred correctly on the scanner table, the CT operator must dictate the specific anatomy over which data is to be acquired during the scan. This process also uses the localiser image. Normally, the operator must move a line manually to the start and end positions of the desired scan. Variations between operators can result in either too little or too much of the anatomy being covered. Operators have the habit to be somewhat careful sometimes, therefore, they often extend the scan range further than necessary. Therefore, some AI algorithms have been trained to accurately identify specific human anatomy from medical images. Based on the examination indication and hence, the instructions selected by the operator, the system can automatically choose the scan range that is optimally centred around the required anatomical coverage. (McCollough – Leng 2020.)

6.3 Protocol selection

The selection of the scan protocol is a process that starts with the referring physician, who asks for a specific scan to diagnose a specific condition or illness. Then the radiologist helps determine what type of medical images are most suitable to diagnose that specific condition. Finally, the operator, who knows all the specific variations of protocols programmed into the scanner for any given condition, chooses the right protocol for the specific modality (for example CT). Currently, AI algorithms are under development that could lead any of these stages via a decision matrix to select the optimal protocol. However, now, a system that also takes needed medication, contrast material, or gating schemes into account, is not available. (McCollough – Leng 2020.)

6.4 Parameter selection

In order to optimise a CT examination, many parameters need to be properly and correctly selected. For data collection, these parameters are related to how the radiation is applied to the patient, how the patient table and x-ray tube move, and whether other special techniques are used during the examination. Currently, some automatic exposure control (AEC) systems use simple machine learning techniques to select the optimal tube current and tube potential. One of the more complex decisions involves setting up the contrast agent injection and scan acquisition time, such that the iodine enhancement is most significant over the specific anatomy of interest during data acquisition. To achieve this, data was obtained, at many times, from many different patients as the contrast was injected and travelled through the patient’s body. Then based on this data, an algorithm can correctly predict the ultimate height and width of the resulting contrast enhancement curve in the patient’s aorta. In following patients beyond the training data, the system can predict the entire contrast enhancement curve using only a few data points on the rising edge of the curve, based upon which the optimal timing of the scan can be set as the contrast is flowing through the patient. Clinical studies have demonstrated better consistency of contrast enhancement over the scan range in parallel to a reduction in the required dose of iodinated contrast agent. The reduction in iodine can be achieved by decreasing the rate of injection, which in turn decreases the risk of damage to the vein. (McCollough – Leng 2020.)

6.5 Image denoising

A thrilling implementation of artificial intelligence in CT is the use of a convolutional neural network-based deep learning approach to reduce image noise. This CT image denoising technique is trained to recognize noise and not anatomical structures, which is afterwards subtracted from the original images to improve image quality and reduce radiation dose. The algorithm was trained with millions of small patches from clinical patient data through the abdomen. For those patient cases, reduced dose images were simulated using a validated noise insertion technique. Therefore, the training set contained simulated low-dose images and images acquired at the clinical dose level. From this data, the algorithm was then taught to find image noise. The reduction in noise is substantial, without any loss of spatial resolution. However, AI networks are trained using specific datasets, which represent specific image characteristics. That's why data acquired on different CT scanner models or with different acquisition or reconstruction parameters typically do not work well with networks that have been trained under different conditions. This lack of generalisability is one of the most fundamental barriers to widespread deployment of deep-learning-based image denoising. (McCollough – Leng 2020.)

7 AI based solutions in CT

7.1 Model Based Iterative Reconstruction (MBIR)

More recently, a more complex iterative reconstruction technique has become clinically available. The model-based iterative reconstruction (MBIR) is an algorithm that reconstructs features of the projection data more accurately based on the noise system and the geometry of the machine. Recent studies on MBIR have also shown that it allows for further dose reduction over ASIR (adaptive statistical iterative reconstruction), while still preserving image quality. Therefore, use of MBIR appears very promising for reduction of radiation dose, particularly in children. Especially in children who potentially receive multiple CT examinations and are at a greater risk of cancer development due to relatively high cumulative doses. (Kim – Yoo – Jeon – Kim 2016.)

Most of the MBIR images with ultra-low dose were on par with the images with standard dose in subjective image quality. The image noise level of MBIR lessened more than 50%, unlike that of ASIR. Adaptive statistical iterative reconstruction is a first-generation iterative reconstruction technique that is broadly used in clinical practice. It provides diagnostically acceptable images with low-dose CT by reducing image noise and overcoming the limitations of filtered back projection, which is not well suited for low-dose CT. Model based iterative reconstruction, on the other hand, which is a fully iterative reconstruction based not only on the noise statistics of photons and electrons but also on the geometry of the machine itself. It is capable of reconstructing the features of the projection data, requiring higher computational demand and longer processing time. While ASIR images can usually be reconstructed in under one minute, the creation of MBIR images takes a lot longer (30–60 min), making it difficult for routine clinical use, especially emergency cases. (Kim – Yoo – Jeon – Kim 2016.)

7.2 Advanced Intelligent Clear-IQ Engine (AiCE)

Advanced intelligent Clear-IQ Engine (AiCE) is a fast, low noise algorithm and a fully integrated DLR (deep learning reconstruction) that not only conserves extraordinary spatial resolution but also simultaneously improves low contrast and noise characteristics. (Boedeker 2019.)

AiCE DLR (Advanced intelligent Clear-IQ Engine Deep learning reconstruction) is a fast reconstruction algorithm including both image domain components and raw data to reduce artifacts and improve the signal-to-noise ratio (SNR) in images. The AiCE DLR features a highly trained, multilayer neural network to lessen the immensity of noise in high resolution images while preserving Precision's detail. The combination of Precision with AiCE DLR allows for Ultra-High-Resolution scanning at standard clinical CT doses for the first time ever. During development, the AiCE DLR algorithm is taught to produce high SNR images through an intense training process. AiCE learns to differentiate signal from noise by training on specific, high quality patient data sets. These are acquired with high tube current and reconstructed with all the advantages of state-of-the-art MBIR, including sophisticated system and noise models as well as many iterations not possible clinically. Because AiCE is trained on images of such high quality, it learns to preserve edge and maintain image detail, which is especially important for Ultra-High-Resolution scanning. (Boedeker 2019.)

One key to a successful Deep Convolutional Neural Network (DCNN) lies in its network structure design, which affects both reconstruction speed and image quality. To achieve the best computational efficiency and enhance output image quality, network structure factors such as number of neurons in each layer, number of network layers, convolution kernel sizes, etc., were fully optimized in the AiCE algorithm. Effective acceleration strategies and memory management technologies were carefully designed and integrated in the system to fully make use of hardware capabilities and maximize reconstruction speed. (Boedeker 2019.)

7.3 Super-resolution convolutional neural network (SRCNN)

SRCNN is a deep-learning-based super-resolution method, which allows for the enhancing of image resolution in chest CT images. It can learn an end-to-end mapping between the low-resolution image and the high-resolution image, and it could improve image quality in high-resolution CT images. (Umehara – Ota – Ishida 2017.)

Deep convolutional neural network (DCNN) has revolutionized the application of many computer vison problems, including image enhancement, like deblurring and denoising. In super-resolution, the super-resolution convolutional neural network (SRCNN) scheme, which is a deep learning-based super-resolution method, has recently been proposed. The SRCNN scheme is capable of learning an end-to-end mapping between the low-resolution image and the high-resolution image. Recent studies have also shown that the use of the SRCNN scheme for non-medical imaging achieved superior performance over previous super-resolution methods in terms of both image quality and processing speed. In medical imaging, it has been shown that the application of the SRCNN scheme to for example, chest radiographs, could significantly improve image quality of high-resolution images in comparison with the use of the conventional linear interpolation methods. (Umehara – Ota – Ishida 2017.)

8 Objective and purpose

The purpose of this thesis is to map out what kind of AI-based solutions there are in CT and what their main benefits as well as disadvantages are. We will do this by researching for articles on the subject and reviewing as well as analyzing them.

The objective is to inform and educate radiographers and healthcare professionals around the world who will benefit from understanding the basics of AI technology and how AI-based solutions, especially those related to convolutional neural networks, can be used in computed tomography imaging, for example to reduce noise and remove artifacts. This thesis is being done for ourselves, our fellow radiography students, our teachers, ICT- healthcare and technologies students, students from the University of Singapore and all radiographers and healthcare professionals who wish to read it.

Our research questions are:

(1) In what ways can artificial intelligence be used in computed tomography?

(2) What kind of AI based solutions are already in use in CT and what are the main benefits and the main disadvantages?

9 Methods

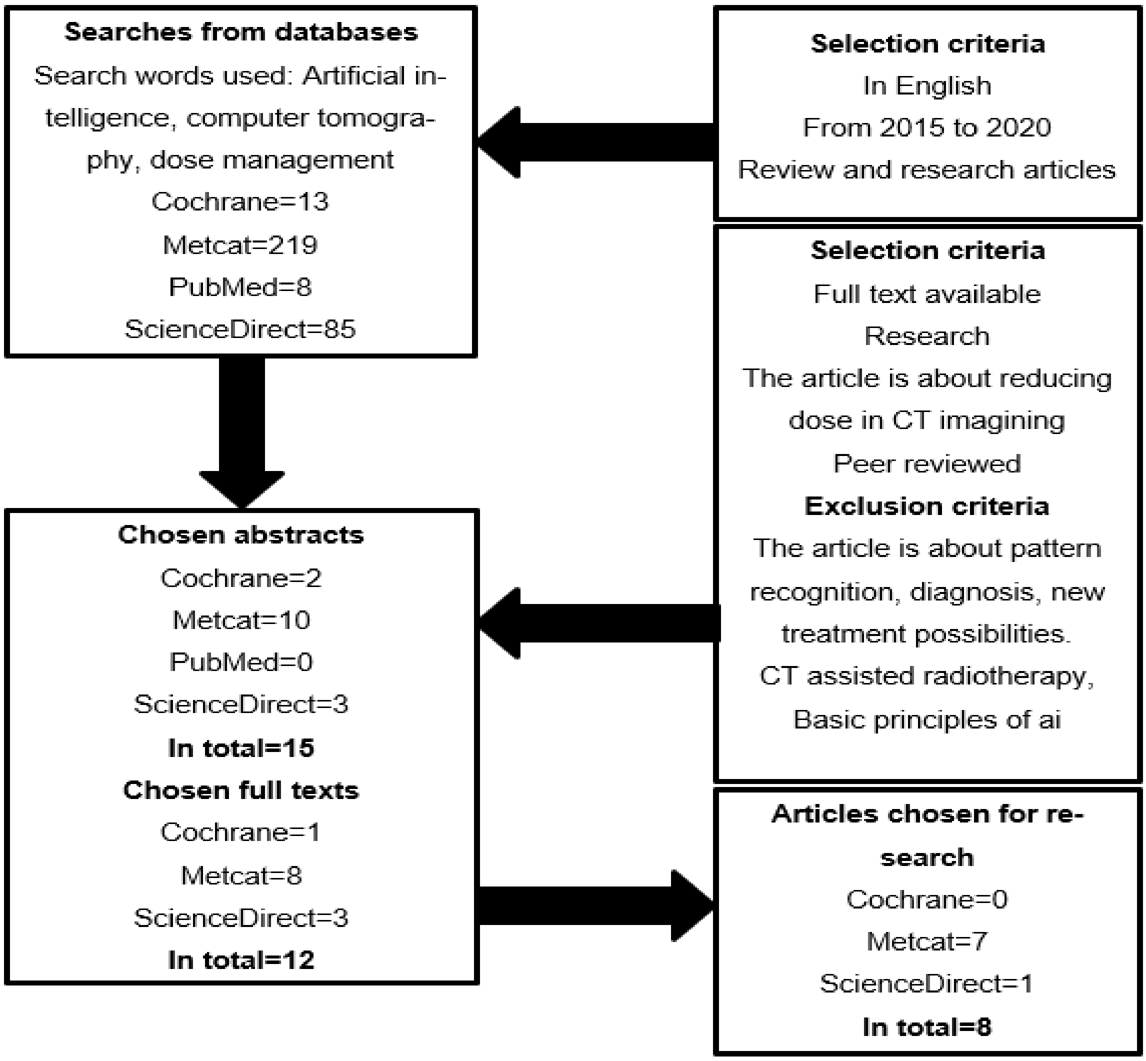
9.1 A literary review

A literary review examines published articles in a specific area of subject within a certain time period. It can be a summary or a synthesis or it can include both. A summary is a recap of the important information whereas a synthesis is a reshuffling of the information. A literary review can also assess the sources and tell the reader on the most relevant information. It could give a new interpretation based on old material or it could incorporate new interpretations with old interpretations. The focus in a literary review, nonetheless, is to summarize and analyze the arguments and ideas in the selected articles, without adding new ideas. (The writing center 2020.)

9.2 Information retrieval

To search for the articles for our thesis, we used several databases for medical science publications (Cochrane, Metcat, PubMed and ScienceDirect). We chose articles that had been peer reviewed and were maximum of 5 years old. This is because there are lots of new research done every year in the field of AI and progress in GPU’s and computing power make development of more complex AI-solutions possible. In the planning phase, we found 8 articles that answer to our research questions. With those articles we could start to work on our thesis and refine our search terms to find more articles for research. Two of the articles found had to be ultimately cut because they didn’t fit our redefined research questions. All in all, the information retrieval was a long and difficult process but, in the end, we found articles mostly fitting to our theme.

We made an information retrieval table that describes our process of searching articles for our research. It shows what databases were used, criteria's for choosing and rejecting articles, how many were found and how many were rejected and selected.



These articles helped us refine our search questions further and we added convolutional neural network to our search terms. We also found articles from references. At this phase we had 12 articles. We dropped 2 because they along with AI it was researching some experimental Hybrid CT methods. We also dropped 4 articles because they were CT manufacturer's own articles.

10 Articles for the review

Articles	Country of origin and year of publication	Writers	Main findings	Benefits and disadvantages
A Deep Convolutional Neural Network using Directional Wavelets for Low-dose X-ray CT Reconstruction	Republic of Korea, 2017	Eunhee, Kang – Junhong, Min – Jong, Chul Ye	CNN based method was superior in denoising low-dose CT's than MBIR.	Their method was effective on reducing noise from low-dose CT images and were able to retain some of the structures. Disadvantage of their method was it was only usable for one dose level. For other doses new training phase was needed. Denoised images had some blurring.
Deep-neural-network based sinogram synthesis for sparse-view CT image reconstruc-tion	Republic of Korea, 2018	Hoyeon, Lee – Jongha, Lee – Hyeongseok, Kim – Byungchul, Cho - Seungryong, Cho	CNN based method can make images from sparsely sampled sinogram that are comparable to full sampled sinograms.	Benefit from this method was that Full CNN was only used in training phase which frees computing power when reconstructing images. Lower noise from Low-dose CT images

Generative Adversarial Networks for Noise Reduction in Low-Dose CT	The Netherlands, 2017	Wolterink, Jelmer M. – Leiner, Tim – Viergever, Max A. – Išgum, Ivana	Their application was able to reduce noise and make determining CAC score more accurate.	Their application needed increased computing power in the training phase. Disadvantages were for example, limited sample size and artefacts caused by patients breathing and moving.
Low-dose CT via convolutional neural network	China, 2017	Hu, Chen – Yi, Zhang – Weihua, Zhang - Peixi, Liao - Ke, Li – Jiliu, Zhou – Ge, Wang	They were able to reduce noise on low dose CT using CNN with only 3 layers.	Using 3-layer CNN they were able to reduce needed computing power. Statistically noised reduction of their method was not significantly higher than other state of art denoising methods.
Competitive performance of a modularized	USA, 2019	Hongming Shan – Atul, Padole – Fatemeh, Homayounieh –	MAP-NN based method images had better noise suppression and	This method was more efficient and produces more accurate

deep neural network compared to commercial algorithms for low-dose CT image reconstruction		**Uwe, Kruger-Ruhani Doda Khera – Chayanin, Nitiwarangkul - Mannudeep K. Kalra - Ge, Wang**	**structural fidelity when compared to IR methods by 3 CT manufacturers.**	**images when compared to already exciting methods.**
Stacked competitive networks for noise reduction in low-dose CT	**China, 2017**	**Wenchao, Du – Chen, Hu – Wu, Zhihong – Sun, Huaiqiang – Liao, Peixi**	**Stacked competitive network (SCN) based denoising method performed best when comparing to other 5 other methods.**	**SCN was most effective in denoising and preserving structures. All of the compared denoising methods caused some blurring on images and loss of structures.**

11 Analysis

In this chapter we do a brief analysis on the articles we chose for our study. We also categorize them based on which AI application they were researching.

11.1 Convolutional neural networks (CNN)

Eunhee Kang, Junhong Min and Jong Chul Ye studied if deep neural networks with directional wavelet approach can be used in removing noise from low-dose CT images and if CNNs can be used in getting training data from large and different types of data. For this they developed their own algorithm and used MATLAB program to simulate image reconstruction.

To test their algorithm's learning and training capabilities, they used data from 10 different patients (3642 slices, 1mm slice thickness). Also, to test de-noising capabilities, they added data from quarter dose images of 20 different patients (2101 slices). From each patient they got routine CT and low-dose CT images with a quarter dose. Regular CT images were used to compare noise from low-dose CT images. From this comparison they created weights for their training nodes. At this point they realized that their computers were not powerful enough to compute full datasets, so they increased slice thickness to 3mm and used only 200 randomly selected slices. When comparing 1mm and 3mm slice thickness images, they noticed that 3mm thick denoised images had preserved their fine details better than 1mm slices. This was most clear with boundaries between organs and details inside organs were clearer. But in exchange, 1mm thick slices showed lesions better, had fewer streaking artefacts, were more blurred and some of the high frequency textures disappeared. (Eunhee – Junhong – Jong 2017.)

When comparing denoised and original images they noticed that CNN was able to remove different types of noise, also edges of different organs and structures were clearer even when images were taken with a quarter dose. For example, in denoised images lung details were easier to see and the vessels in the liver were seen more clearly. (Eunhee – Junhong – Jong 2017.)

Hu Chen, Yi Zhang, Weihua Zhang, Peixi Liao, Ke Li, Jiliu Zhou and Ge Wang wanted to find out if it's possible to reduce noise from images. Their proposed CNN network had only three layers, which is why it was able to produce good results on a fraction of the needed computational power when compared to more complex CNN networks. When processing their data, they focused on radiation dose, training data and testing data.

They used 7,015 routine CT images from 165 different patients. These images were acquired from the national cancer imaging archive (NCIA). From these images 200 were chosen as the training data and 100 different for testing their method. Data was applied for training in patches. (Hu – Yi – Zhang – Peixi – Li – Jiliu – Ge 2017.)

To compare their method, they used three other reconstruction methods, ASD-POCS, K-SVD, BM3D. They simulated their data with MATLAB. Findings were analyzed by comparing PSNR, RMSE, SSIM values of images and by inspecting them visually. For visual inspection, chest and abdomen images were chosen. ASD-POCS caused blocky artefacts. KSVD and BM3D were unable to remove streaking artefacts near bones. Their CNN method was able to remove most of these. When doing quantitative comparison of these methods, CNN performed best on all the cases, expect SSIM on abdomen images. They speculated that this might be because the abdomen has lots of soft tissue and

BM3D is specialized on that area. All the image denoising and reconstruction methods improve image quality. CNN method had best results and were the closest to the original images. These images were then shown to three radiologists who scored said images. Result were comparable to their own findings. (Hu et.,al 2017.)

After this they repeated the training phase again with different data and weights. This showed that the more varied the training data is, the better it is at denoising, especially in high noise images. After this experiment they increased the amount of data used in the training phase (twelve times the data). This caused some structures to become clearer than before and it also caused the CNN to become better at reconstructing images that have varying noise levels. (Hu et.,al 2017.)

All of these previous tests were generated on numerical simulation (MATLAB).

Jelmer M. Wolterink, Tim Leiner, Max A. Viergever and Ivana Išgum also studied if U-Net based CNN can be used to reduce noise from low-dose CT and especially how it denoises calcium deposits in coronary arteries.

Training of the CNN application that they created for this study was two phased. In the 1st phase (generator CNN), it analyses low-dose CT images and denoises them and after that it attempts to align both images by their first voxel to minimize differences and compares them. In the 2nd phase (discriminator CNN), it analyzes similarities from the images and gives feedback to the 1st phase, which then improves its ability to align images and correct artefacts/missing data. (Wolterink – Leiner – Viergever – Išgum 2017.)

To test their CNN method, they did normal and low-dose CT (1/5 of the dose) scans to anthropomorphic thorax phantoms. In these they placed two artificial coronary arteries that had hydroxyapatite inside to simulate calcification. The phantom was scanned five times and between scans the phantom was rotated to change the distribution of the hydroxyapatite. They also had CT (routine and 1/5th dose) scans from 28 volunteering patients. To compare results, they used the mean and standard deviation of Houndsfield unit (HU) in region of interest (ROI), peak signal to noise ratio (PSNR) and mean squared error (MSE). On patient’s images they compared agatston score and calcium artery calcification (CAC). They used filtered back projection to reconstruct their images. (Wolterink – Leiner – Viergever – Išgum 2017.)

Their experiment showed that using discriminator CNN (2nd phase of their training network), they were able to create low-dose CT images that were like routine CT images. The feedback that the 2nd phase gives, prevents image reconstruction from smoothing the image so low-density calcifications can be discovered more accurately. When processing cardiac patient’s data, CNN had troubles on aligning routine and low-dose CT images, which causes some changes on images and noise. They assumed that this was caused by patient movement and breathing. They noticed that the AI-application was able to learn to reduce noise caused by this phenomenon. (Wolterink – Leiner – Viergever – Išgum 2017.)

Hoyeon Lee, Jongha Lee, Hyeongseok Kim, Byungchul Cho and Seungryong Cho also studied CNNs but instead of using it to denoise images, they researched if it was possible to restore missing data in sinograms. They created their own CNN for this project, and it was based on a residual U-net model. In their study it was determined that when training CNN, adding higher weights to measured- and correlating pixels was more important than giving them to missing pixels. After denoising they were able to take CAC value from six patients’ images that were impossible before. Generally, denoised images had lower CAC score than routine images.

Data they used in their research was from seven different patient's lung CT-scans. Number of slices was 634. Using this data, they re-sampled the original sinogram to make a sparsely view-sampled sinogram. This new sinogram had only a quarter of the original’s views. This new sinogram was also upscaled to the original’s size. Training data was applied in patches to lower the required computing power and increase amount of data given for training at the same time. (Hoyeon – Jongha – Hyeongseok – Byungchul – Seungryong 2018.)

To test their CNN’s performance, they compared it to the original base sinogram, sinograms made with two analytic interpolation methods (linear interpolation method and directional interpolation method) and another CNN network. In this study, they got data from eight patient’s lung-CT datasets. Number of used slices was 662. None of these patients were part of the training phase. All sinograms were created with identical values. Sinograms created with CNN’s (CNN 20 and U-NET) resembled original sinogram more than other methods. To compare results, they computed root mean-square-error (NRMSE), peak signal-to-noise-ratio (PSNR) and structural similarity (SSIM). When comparing these CNN's based applications performed better than other methods. Differences in CNN 20 and U-NET were small, but U-NET was better at restoring missing data. They assumed that this was because in their training, it was determined that when restoring missing data, it's weight and values don't change. (Hoyen et.,al 2018.)

Images were reconstructed using Filtered back projection (FBP) algorithm. From each patient's dataset, seven different images were created using different sinograms. These were: original, sparsely sampled sinogram, linear interpolation, directional interpolation, CNN with 20 convolution layers and U-net. They also tested iterative image reconstruction algorithm that was able to create image from sparsely sampled sinogram (POCS-TV). When visually comparing reconstructed images. Images created from sparsely sampled sinogram had lots of streaking artefacts. Images crated from POCS-TV had cartoon artefacts and didn't show small structures. Two analytic interpolation methods had some streaking artefacts. Both CNN based images showed little streaking artefacts. When comparing NRMSE, PSNR, SSIM and visual quality, the U-net based CNN performed best in all tests. (Hoyen et.,al 2018.)

11.2 Modularized adaptive processing neural network (MAP-NN), Stacked neural networks (SCN)

Hongming Shan, Atul Padole, Fatemeh Homayounieh, Uwe Kruger, Ruhani Doda Khera, Chayanin Nitiwarangkul, Mannudeep K. Kalra and Ge Wang studied if deep neural networks perform better than modern iterative construction methods and establish foundation for CT reconstruction algorithms that can be developed further with data and deep learning. For this study they chose modularized adaptive processing neural network (MAP-NN) based denoising method on low-dose CT. This approach decomposes networks into smaller identical network modules. Each of these networks creates small improvements on denoised images. Advantages of the MAP-NN over CNN based methods is the fact that CNN can only make denoised images from low-dose CT images but MAP-NN can also be used to reduce noise from routine CT images. In practical use of MAP-NN, radiologists can use software to see and browse denoised images produced by these network modules and choose the image that they find most useful.

For this study they got scans from 60 different patients and three different manufacturers (Siemens, Philips and GE). Order of manufacturers was randomized and renamed (A, B, C) to hide the identity of the manufacturer. Sinogram data for low-dose CT scans was constructed using IR-, FBP and MAP-NN methods, six images in total. From each patient two images that had noise and artefacts were chosen. Then these images were evaluated by three radiologists and they ranked them in the order of which they preferred. When comparing results, with manufacturers A and B, all radiologists scored MAP-NN over IR methods on abdominal images. On chest scans MAP-NN and IR methods were comparable. Also, IR abdomen images by manufacturer A and B were deemed unacceptable or limited while MAP-NN images were accepted. With manufacturer C's abdomen and chest images, MAP-NN was statistically comparable to IR methods. On body scans, all radiologists expect one scored MAP-NN better. The one radiologist scored IR and MAP-NN comparable. (Shan – Padole – Homayounieh – Kruger – Doda Khera – Nitiwarangkul – Kalra – Wang 2019.)

For the quantitative study, images were scored based on noise suppression and structural fidelity. MAP-NN scored significantly better than IR methods in both categories.
As a conclusion, MAP-NN performs better or comparable in noise suppression and structural fidelity when compared to three manufacturer's IR methods. (Shan et.,al 2019.)

Wenchao Du, Chen Hu, Wu Zhihong, Sun Huaiqiang and Liao Peixi studied Stacked neural networks (SCN). SCN consists of several successive competitive blocks (CB). These enable the network to make multiscale processing.

They compared SCN to five other denoising and image reconstruction methods (TV-POCS, K-SVD, BM3D, SSCN, KAIST-net). From constructed images they did a quantitative comparison of peak signal to noise ratio (PSNR), root mean-square-error (RMSE) and structural similarity (SSIM). All experiments were done in MATLAB software. The data they used consisted of 7015 routine CT images from 165 different patients. These images were of different parts of the body. From these images they created low-dose CT images by introducing Poisson noise projection to routine CT images. From these images they randomly chose 200 pairs of routine and low-dose CT images for training and a 100 for testing. (Wenchao – Chen – Wu – Sun – Peixi. 2017.)

All of the compared methods were able to reduce noise and artifacts from the images but their effectiveness on different structures varied. SSCN, KAIST-NET and SCN were able to remove most of the artifacts and noise from the images, and they also were able to maintain the majority of the structural information. SCN was best at distinguishing low-contrast regions. When comparing abdominal CT images, SSCN, KAIST-NET and SCN again performed best, being able to remove most of the artefacts and noise, while only suffering from small blurring. SCN was able to show structural details from the liver, vertebral Colum and bones. They also did a quantitative comparison of each method using PSNR, RMSE and SSIM. SCN performed best on all measurements. When statistically comparing it to SSCN and KAIST-NET, the difference wasn't significant, but BM3D, K-SVD and TV-POCS were significantly worse than the other three. (Wenchao et.,al 2017.)

To further test their method, they did the same test using dataset from Mayo clinical dataset (this data was made available for free use on their AI competition). Again, on visual comparison, SCN performed best on noise reduction and structure preservation and measured best in quantitative comparison. To further test their method, they experimented by changing the number of kernels in competitive blocks. They noticed that increasing their number made the method better, but in exchange this would increase training time and the need for higher computational power. They concluded that three kernels in a competitive block was the most cost-effective solution. (Wenchao et.,al 2017.)

12 Results

Our research questions were:

(1) In what ways can artificial intelligence be used in computed tomography?

(2) What kind of AI based solutions are already in use in CT and what are the main benefits and the main disadvantages?

12.1 In what ways can artificial intelligence be used in computed tomography?

AI-solutions can be widely used in CT, for example to help in protocol selection, patient positioning, parameter selection etc. but the ones we were truly interested in were those that are able to reduce noise, artefacts or reconstruct Low-dose CT images. Typically using Low-dose CT, it reduces image quality by having low signal noise ratio (SNR). AI-solutions aim to reduce that noise from the images. Conventional de-noising solutions have problems with removing low-dose CT specific artefacts. AI based methods could be used in restoring that missing data. They could also be used in assisting radiologists to analyze images by highlighting anomalies and segmenting images.

12.2 What kind of AI based solutions are already in use in CT and what are the main benefits and the main disadvantages?

Often AI-solutions are at the stage of computer simulations. CT manufacturers have AI-solutions on their newer CT-machines for example, GE's true fidelity and Cannon's AICE. Methods that are in use or are close to having practical use are often MBIR and IR based. Those often have simple algorithms and training phases, so they don't need as much computational power as more sophisticated algorithms, which makes them faster.

In our study most of the articles were about Convolutional Neural Network based methods and other Deep learning network based (MAP-NN and SCN).

Challenges that came up for using CNN's were that the computer's processing power was often insufficient. To bypass these computing power limitations, thicker slice size was used. In the study by Eunhee et.,al they also chose 200 random slices from 3642 slices. In Hoyong et.,al's study they found that when inputting training data in patches, it reduces the time it takes to process it and lowered computing power requirements are required. For their study they used patch size of 50. Patch size is gear dependent so what works for someone's application might not be viable for someone else's.

Another problem that was encountered was the fact that the training phase needs to be done separately for different doses. For example, Eunhee et.,al's study used quarter dose CT images, so their application then can't be applied for other doses without doing another training phase. They had ideas that this can be changed by adding more functions into their algorithm. The method had simpler CNN that only had three layers, which meant that it was able to remove noise while needing less computing power. Adding more layers to a CNN, makes it better in its function but it also raises time issues and needed computing power. This also applies on other Network based methods i.e. adding blocks and kernels to SCN. Wolterink et.,al's method had part of its network only working on the training phase, which led to shorter processing time and needed computing power on image reconstruction.

Hoyeon et.,al's study found that they can create from partial sinograms images that were comparable to images created from full sinograms.

The training phase offers many challenges. More data it gets, the better it gets. If the training phase lacks data, the reconstruction phase might ignore data that is crucial. More data it gets though, also the more computing power it needs.

Generally, CNN based methods performed well on denoising and restoring structures in low-dose CT images. Also, they can restore missing data efficiently. Most of AI-methods have blurring on low noise areas, so Wenchao et.,al studied if a SCN based method had good results in removing these. Most of the needed computing power is used in the training phase, and at current hardware depending from used data size, training phases took from tens of hours up to even 12 days. Image reconstruction time is faster than in IR based methods. Methods on these studies performed visually and statistically better than other methods (IR) they were compared to. Usually, good structural fidelity is more desirable than low noise. Which gives a challenge; when removing noise, it weakens structural fidelity.

In Eunhee et.,al's, Hu et.,al's and Wenchao et.,al's studies, they all used MATLAB to simulate image reconstruction. This might cause errors with data since MATLAB is not optimized for deep learning applications yet. This means that simulations might not always resemble real scans or data.

13 Conclusions

The results from these studies is that artificial intelligence has a high potential for use in medical imaging, specifically in CT. Especially the ability to take low-dose CT scans and reduce noise and artifacts in order to get results that are comparable to routine CT scans. This also makes it possible to reduce a patient's radiation dose without sacrificing image quality, which is the goal in every medical imaging due to the ALARA principle.

Problems that deep learning-based denoising methods have is the fact that the denoising process also removes some data that could have been useful and potentially adds blurring to the images. Another problem that arose is the fact that training an AI application needs lots of data. Acquisition of this data has problems, since there is patient confidentiality issues and CT manufacturers sometimes do not share their full data.

AI provides lots of interesting options for further research. Different networks and algorithms could be refined further which makes these applications more effective and less demanding for hardware. You could research different parameters, architectures and number of layers that makes your network most efficient. These applications could be made to specialize on certain artefacts like metal, optimize application for specific body parts or certain manufacturer's hardware.

14 Ethicalness and reliability

We worked on this thesis abiding by good research ethics such as honesty, objectivity, openness, integrity, legality and responsibility. We carefully and critically examined our own work as well as the articles chosen for the thesis. We referred to all the material we used, and we were unbiased while analyzing the articles. The credibility and reliability of the authors of the used articles was protected through the analyzing process. The results were represented without distortion and only reliable resources were used in the information retrieval. All the used material was looked through by both writers and the workload was evenly divided. All decisions were made together, as well.

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